A game theory model of the physician preference item supply chain

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A game theory model of the physician preference item supply chain

by

Cara J. Dienes

A dissertation submitted to the graduate faculty in partial fulfillment of the requirements for the degree of DOCTOR OF PHILOSOPHY

Major: Industrial Engineering

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1. Introduction

1.1 Problem Description

Hospitals use many types of supplies, including medical devices, pharmaceuticals, capital equipment such as medical imaging equipment and laboratory fixtures, and commodity items such as gloves, intravenous solutions, and syringes (Schneller & Smeltzer 2006). While best practices in supply chain management have been used successfully for commodity items, management of the medical device supply chain continues to be problematic. Many types of one-time use medical devices (e.g., orthopedic implants, stents, and pacemakers) have significantly higher costs and more frequent product innovations, than the commodity items. In 2008, the Fredonia Group estimated that the orthopedic implant industry and the cardiac implant industry value totaled $25 billion dollars (Fredonia 2009a; Fredonia 2009b). Purchasing these types of specialized supplies is primarily driven by the preferences of individual physicians based on their expectations of the clinical outcome and the physician's familiarity with the specific product or brand (Schneller & Smeltzer 2006; Burns 2002; Montgomery & Schneller 2007; Wilson et al. 2008). These physician preference items (PPI) have been recognized as a major contributor to hospital supply chain costs (Wilson et al. 2008; Schneller & Smeltzer 2006; Robinson 2008). PPI supplies are produced by device manufacturers who market their goods directly to physicians.

The physician-manufacturer supply chain relationship is unique to healthcare systems. Manufacturers have used the strategy of introducing their brand to physicians early in their career to establish a long term relationship, thus benefiting from physicians’ continued use of product lines that were used during their residency (Burns et al. 2009). In addition to this, manufacturers may offer additional device training to physicians and, in some instances, will send a representative to deliver the product in just-in-time fashion to provide the device as well as expertise to the physician in the operating room during a procedure (Schneller & Smeltzer 2006). PPI manufacturers also cultivate relationships with physicians in order to recruit them as consultants. They rely upon physician consultants to participate and assist in product design, as well as clinical trials, for which the physicians may receive both intangible benefits and financial compensation, (Burns 2002; Schneller & Smeltzer 2006). Because product design is one dimension that PPI manufacturers compete on, updated versions of PPIs are released frequently to offer new features (Burns 2002). Many authors such as Schneller and Smeltzer (2006) have suggested that some types of medical devices have a relatively high rate of product development, as compared to other industries. According to Joshi, suppliers "routinely" develop new generations of certain PPIs with only incremental improvements (Joshi 2008). However, some product updates incorporate more new technology than others.
Physicians must sort through new product generations to determine which updates warrant a change in their methods, and which do not, in order to maximize their efficiency and provide high-quality care to each patient.

Like the physician, the hospital hopes to provide high quality patient care, but the hospital-physician relationship places the two parties somewhat at odds. Unlike customers in most industries, physicians do not directly purchase the PPIs. Instead, the hospital at which the physician is performing the procedure will purchase the PPI for physician use (Montgomery & Schneller 2007; Robinson 2008). Physicians value their ability to select a PPI for their procedures, and studies and trade publications (Barlow 2008; Montgomery & Schneller 2007; Robinson 2008) suggest that that price is generally not a consideration when physicians determine their preferences. In contrast, the hospitals, which must pay the difference between the PPI procedure cost and the insurance reimbursement, are understandably sensitive to the price of PPIs, which can be significant. For example, for some orthopedic procedures the PPI costs can be up to 40-80 percent of the reimbursement received, according to industry reports cited by Hariri et al. (2007) and Montgomery and Schneller (2007). In addition to this challenge, in regions with multiple hospitals, physicians are able to select the facilities where they perform a given procedure and may consider the availability of a PPI at a facility when determining where to admit patients (Burns et al. 2009; Robinson 2008; Schneller & Smeltzer 2006; Wilson et al. 2008). Aside from handling the cost-technology tradeoff to satisfy physicians, hospital executives also face the trend of confidential PPI pricing, enforced by the PPI manufacturers’ inclusion of a confidentiality clause within purchasing contracts. These clauses prevent the hospital from sharing PPI price information with third parties. When price information is not shared with third parties, the PPI average price and price variance increases across purchasing hospitals (Neil 2006; Lerner et al. 2008; Pauly & Burns 2008).

Hospital material managers and other administrative decision-makers are attempting to contain the cost of PPIs via one or more mechanisms. Although PPI standardization at a facility may be accompanied by the risk of losing physicians, there has been a push by hospital administrators to create value analysis teams, which may include physicians, with a goal of standardizing vendors and/or product lines for types of PPIs (Schneller & Smeltzer 2006; Wilson et al. 2008). However, these teams are working to standardize preferences that have been engrained in physicians since the start of their career and are influenced by incentives for physicians to build and maintain relationships with specific PPI manufacturers. Additionally, when handling frequently updated PPIs, these teams must assess the clinical value of a barrage of new products and product updates. Unfortunately, many authors report that comparison data (necessary for evaluation) of the clinical value across product offerings is almost nonexistent (Joshi 2008; Schneller & Smeltzer 2006). Another approach
is for hospitals to purchase PPIs via their memberships in group purchasing organizations (GPOs), which buy medical supplies in large volumes and pass on some economies of scale to member hospitals (McKone-Sweet et al. 2005). However, Burns and Lee (2008) report that about 92% of the hospitals responding to their survey purchased less than 75% of their PPIs via GPOs or other purchasing alliances. Nearly 70% of the respondents reported that they purchase less than 50% of their PPIs from GPOs. Finally, some trade publications have suggested that gainsharing, a new concept of sharing a portion of financial benefits from hospital cost reduction initiatives with physicians, is another strategy that hospitals may use to tame PPI expenses (Ketcham & Furukawa 2008; Wilson et al. 2008). Gainsharing has generated controversy (e.g., MacVaugh (2005)) and requires Food and Drug Administration (FDA) involvement. Opponents suggest that it may be a conflict of interest for physicians, who could have personal gains for selecting cost-effectiveness over clinical results.

Finally, as described by Joshi (2008), some hospitals have begun to develop and present "crosswalks," which focus on disseminating PPI price information and product attribute comparisons to the clinical staff.

While a large number of hospital PPI cost control strategies have been suggested and more could be conceived, all of the common methods reported within the trade publications support one or both of the following two objectives: (1) to reduce the number PPI types (brands) purchased, in order to gain volume discounts, and (2) to influence physicians to consider price when determining their preference for a PPI. There is a general lack of research literature on quantitative models for the PPI supply chain. Additionally, little research has focused on the effects of a manufacturer’s product update pace upon other supply chain members. The objectives of the this study are to understand

- to what degree an average physician’s capacity to learn about an updated PPI affects the manufacturer’s optimal product update pace,
- how the optimal value of the product update pace is affected by the manufacturer’s decision to provide a sales representative (“sales rep”) to train and assist the physician,
- and how the optimal value of the manufacturer’s product update pace is affected if the hospital attempts to control costs by limiting the physician's adoption of a product update,

so members of the PPI supply chain can make better decisions, and healthcare policy makers can better understand the impact of their policies.
1.2 Motivation

Given the growth of both PPI usage and prices, the unbalanced financial performance of the hospitals and PPI manufacturers, and the hospitals’ need to select between a wide variety of cost control strategies, and the broader role of technology in systemic healthcare cost concerns, a deeper investigation of the effects of product updates upon the PPI supply chain is warranted. Additionally, studying product update decisions within the PPI supply chain can provide insights on the impacts of product transitions upon supply chains, in general.

As the number of patients affected by PPIs continues to grow, it will become increasingly important to understand the PPI supply chain. For example, this growth is evidenced in hip and knee arthroplasty, specifically. Kurtz et al. (2007) reports that the number of primary hip replacement procedures is expected to grow 182% from 2003 to 2030, up to 572,000 procedures. Even more growth is predicted for primary knee implants, with an expected 3.48 million procedures to be performed in 2030, or 766% growth over 2003. Additionally, the prevalence of high-technology items selected by physicians may spread to other specialties as technology evolves (Joshi 2008). A quantitative study of the PPI supply chain will assist decision-makers by providing insights into cost control measures as the usage of PPIs increases.

Typically, as innovations spread through a market, prices decay over time, as described by Druel et al. (2009). However, despite the diffusion of PPIs, this has not occurred. On the contrary, the price for the devices has exhibited an upward trend. Based upon 45 hospitals within a research network, Mendenhall (2006) reports that orthopedic implant supply costs demonstrated a 5 to 20 percent increase in average price between 2004 and 2005. The trend of increasing prices has been partially attributed to the growth of price confidentiality clauses, in which manufacturers legally restrict their direct customers from sharing price information with any other party.

This increase in the PPI prices, as well as the growing usage of the related procedures, is a practical concern for hospital administrators, because the reimbursements received by hospitals for the PPI and associated procedures have grown much less rapidly, or perhaps even declined (Montgomery & Schneller 2007; Burns et al. 2009; Wilson et al. 2008; Mendenhall 2006). In stark contrast to the perspective of hospitals, whose margins are squeezed between the relatively constant insurance reimbursement of PPIs and the ever-increasing price of the same, PPI manufacturers have achieved financial success. Joshi (2008) highlights the outstanding financial success that healthcare suppliers are experiencing, including some manufacturers of common PPIs, and Kruger (2005) provides an excellent overview of the unique characteristics that enable the PPI sector’s success. This success is exemplified by Stryker and Zimmer, two of the leading suppliers of orthopedic implants, who reported gross profits of
$4,586.8 and $3,123.8 million, respectively, in 2008 (Stryker 2009; Zimmer 2009). With the magnitude of these profits, it is no wonder that the device manufacturers have the resources required to fuel the development of innovative, new products, in addition to creating improved versions of existing devices. By investigating the effects of product update pace on hospital costs, this work provides further understanding of the financial pressures felt by hospital executives due to PPI supply costs.

As PPI manufacturers increase the variety of product options, hospitals need effective PPI cost containment approaches to deal with the physician's demand for newer and better PPIs and the PPI manufacturer's financial motivation. Medical trade publications recommend a variety of PPI cost control strategies for hospitals, but little discussion on when hospitals should select one approach over another has been presented. A single hospital likely belongs to a different supply chain for each specific PPI within a multitude of fields, such as orthopedics, cardiology, and neurology. While a hospital may find a cost control strategy that works well with one type of PPI, it may not be the most effective strategy for another PPI procured by the same hospital. Furthermore, some of the most frequently mentioned strategies, such as value analysis teams and crosswalks, require a team of hospital staff, physicians, and/or nurses to perform product assessments and comparisons. These approaches are resource intensive and may have difficulty keeping up with the fast pace of PPI markets. Using a quantitative approach, this study provides a foundation for understanding the PPI supply chain so that future efforts can investigate the effects of volume discounts and physician price sensitivity upon hospital PPI costs. These insights can assist hospital decision-makers, physicians, and members of the healthcare community who are attempting to balance the desires for cutting edge care and reduced costs.

Hospitals face a fast pace, complex scenario as members of PPI supply chains, in which physician incentives from the manufacturer, the availability of just-in-time PPI delivery and on-site training, the level of price transparency, and the possibility of obtaining volume discounts (via a GPO or from a manufacturer directly) are all factors that contribute to their PPI supply costs. The effects of a high PPI product update pace, specifically, are important for in-depth analysis because the tradeoff between cost effectiveness versus product innovation apparent in the PPI supply chain is representative of the conflict between accessibility of and technological advancements within the U.S. healthcare industry at large. The Congressional Budget Office (CBO) reported upon the effects of innovation upon health care costs in its paper *Technological Change and the Growth of Health Care Spending* in January 2008. This government study found that, "Technological innovation can theoretically reduce costs and, for many types of goods and services, often does. Historically, however, the nature of technological advances in medicine and the changes in clinical practice that followed them have tended to raise spending." The CBO continues, reporting that around half of the increase in health care costs can be attributed to technology improvements, even when considering other issues such as an increase in prices, as well as demand due to wider insurance coverage. However, as the resulting inflation of health care costs from
developing new technology is not favorable, it is similarly undesirable to stifle product innovation and technological advancements.

Although the observations made by the CBO are for the healthcare system at large, they reflect the cost-innovation tradeoff experienced by the PPI supply chain members. By researching how this tradeoff impacts hospital costs and manufacturer profits within the PPI context, this research contributes to a further understanding of how innovations may impact the health care system, in general. Additionally, benefits from reducing a hospital's PPI expenses include reducing costs for the hospital and patient, which supports the overarching goal of improving accessibility and affordability of healthcare. And as Joshi observes, "As medical device technology continues to advance, driving more of the hospitals clinical cost base towards physician preference items, efforts to build the foundation for effective physician engagement will be well rewarded," (Joshi 2008). Likewise, as innovative products become integral to the treatment of certain conditions, it becomes more crucial to understand how manufacturers' decisions may be driving up prices by setting an artificially high product update pace, and how hospitals can address PPI cost control.

Outside of the healthcare context, product update pace is deserving of further investigation, in order to develop insight into how it impacts supply chains, in general. Opportunities to build upon the understanding of product update pace are discussed in detail in Chapter 2, Literature Review.

1.3 Research Questions

This study addresses the following research questions:

1. When the hospital is passive, how does the average physician's capacity to assimilate knowledge about the PPI update affect the manufacturer's optimal product update pace?

   **Hypothesis:** When the hospital is passive, the average physician's capacity to learn about the PPI update creates an upper bound on the spread of the product update amongst the physician population, which decreases the frequency of the manufacturer's optimal product update pace.

2. When the hospital is passive, how is the optimal product update pace affected by the manufacturer providing a sales rep to train and assist the physician?
Hypothesis: By providing a sales rep to train and assist the physician, thus increasing the physician's capacity to adopt a PPI update, the manufacturer can increase the optimal frequency of releasing its product updates.

3. If the hospital attempts to control costs by limiting the physician's adoption of a product update, how are the optimal values of the manufacturer's product update pace and the average physician's adoption time decision affected?

Hypothesis: When the PPI update provides a small clinical improvement over the current product version, and the hospital implements a cost control policy restricting the physician's adoption of a PPI update, the manufacturer's ideal time between product updates and the average physician's optimal adoption time both increase.
2. Literature Review

The contributions of this work build upon several streams of existing research in the areas of product update timing decisions, product rollover decisions, relationship marketing decisions, and hospital PPI cost control policies. Related work in each of these areas is summarized in this section.

2.1 Product Update Timing Decisions

A number of researchers have used analytical models or empirical investigations to study a firm's new product introduction timing. These efforts can be categorized into those which consider a firm's internal factors and those which incorporate factors external to the firm in the decision making process. Much of the work in this area has focused on new products, whereas others consider the timing of incremental improvements by the release of new versions, or generations, of a product. Given that the focus of this research is on the release of new versions of a product, only the literature on incremental product improvements is summarized here.

The time-pacing strategy, a paced product update approach, has been proposed by several authors (Eisenhardt & Brown 1998; Christensen 1997) to simplify and coordinate the many activities required for a firm to develop and launch a new product or product version. Christensen (1997) presents a discussion of the benefits that a firm may experience from implementing a time-pacing strategy in a Harvard Business Case about Medtronic, a major pacemaker manufacturer. Medtronic found that by defining the product update pace \textit{a priori}, it was able to reduce last-minutes changes to upcoming product updates, because team members were aware of when their newly developed features must be ready to be incorporated into another product update. Eisenhardt and Brown (1998) contrasted the proactive nature of time-pacing versus the reactive nature of event pacing and discussed the benefits of having a predictable rhythm of change within an organization. They suggested that setting the right pace for the industry is important, depending upon seasonal trends and other common ebbs and flows within an industry, and they highlighted the usefulness of product design modularity in meeting the scheduled pace. In previous work, product update pace is tied to the term \textit{clockspeed}, attributed to Fine (1998). The term was introduced to convey the concept of the rate of change within a business environment. Three sub-metrics were defined that contribute to an industry's clockspeed: 1) \textit{process clockspeed}, which describes how fast the production technology and processes change, 2) \textit{organizational clockspeed} which describes how quickly a firm's organization structure and leadership evolves, and 3) \textit{product clockspeed} which describes the rate of new product releases and updates. In subsequent work, authors have related the product clockspeed concept to the product update pace that is driven by a firm's product introduction timing decisions. However, the concept of clockspeed is more commonly used to characterize an industry, rather than to describe a product development strategy such as the time-pacing, as defined by
Christensen (1997) and Eisenhardt and Brown (1998). In this work, the term product update pace, is used to describe a constant pace defined by a firm applying the time-pacing strategy. The term product update interval is used to describe the time between updates to achieve the desired product update pace. The term clockspeed is used only when citing related literature which utilizes the term.

Prior to the work of Christensen (1997) and Eisenhardt and Brown (1998), few studies addressed the time-pacing strategy or the product update timing decision. An exception to this can be found in the work of Wilson and Norton (1989), who modeled a firm's optimal timing for the release of a durable product update, considering the time for the products to diffuse throughout the market within a monopoly. They addressed the time between the releases of only two product versions during a specified planning time, and did not incorporate details such as the product rollover of the first generation. Working under the assumption of constant profit margins, they concluded that in many cases, the manufacturer should update the product immediately.

Similar to Wilson and Norton's study, this research considers how the product update pace relates to other members of the manufacturing firm's supply chain, and will not address how that pace impacts internal processes. However, this investigation differs from Wilson and Norton's analysis in several ways. First, while their analysis was limited to durable goods which consumers do not replace frequently, our model considers the consumable nature of PPIs, from the physician's perspective. While implants and other PPIs may be durable from the patient's point of view, a physician consumes a product with each patient. Secondly, Wilson and Norton assumed a constant profit margin, which is contrary to the nature of increasing prices (and margins) experienced by PPI manufacturers. Additionally, we will allow for the planned discontinuation of the previous product version, via the incorporation of a product rollover policy decision.

Following the work of Christensen (1997) and Eisenhardt and Brown (1998), many authors have studied some blend of Fine's clockspeed concept and a firm's product update timing. Mendelson and Pillai (1999) studied the clockspeed-product introduction decision empirically, and developed metrics for industry clockspeed, based upon the Bass (1969) product lifecycle function. Their data, collected from electronics manufacturers over a span of 4 years, demonstrated that industries with higher clockspeeds tend to have a higher rates of organizational change and "product redesign". Additionally, they found that in industries with higher clockspeeds, product lifecycles are "compressed", and firms have shorter project duration for comparable product complexity. Souza et al. (2004) supported these findings with an analytical model which treated industry clockspeed as an external environmental condition by assuming a given price decay within the industry. Within this context, they investigated the effects of industry clockspeed upon a
firm using a Markov decision process to capture the rate of new product introductions and product quality as decision variables. They found that the best pace for new products is a function of the clockspeed of the firm’s industry, while the ideal product quality decision is based upon characteristics of the firm itself. Furthermore, they determined that although the time-pacing strategy is not always optimal, it will "perform well under many conditions."

Interjecting competition into the scenario, Souza (2004) studied the strategic nature of product introduction timing using a game-theoretic approach. Assuming a duopoly competing upon a "dominant product design" with small product improvements, he demonstrated that firms higher costs, lower profits, and lower market share is competitive at slower clockspeeds than a more successful firm in the industry. In this sense, he reported that, "a firm’s strategy should be consistent with its capabilities." Souza also incorporated learning into his analysis, from the manufacturer's viewpoint. He found that manufacturing learning corresponds to a higher product introduction rate and a reduction in the competitor’s profitability. In contrast to Souza et al. (2004), Carrillo (2005) considered a firm's product introduction speed as a contributor to its industry clockspeed, analyzing the "interplay" between the firm's product update pace decisions and its industry's aggregate clockspeed. Using a decision-theoretic approach, her model was used to study how frequently a single firm should release new products, assuming that a firm will have only one product generation on the market at a time. Like Souza (2004), her results indicated that a firm’s optimal pace is driven by its role in the marketplace, as well as its financial performance.

Mendelson and Pillai (1999), Souza et al. (2004), Souza (2004), and Carrillo (2005) each provided insights into the relationship between a firm’s product introduction timing and industry clockspeed. However, their product timing decision insights were based on a firm’s cost-reducing, profit-maximizing behavior. This research incorporates the manufacturer’s profit-maximizing behavior indirectly, through a representation of sales volume and product value. While the aforementioned authors concentrated on the effects of internal costs on the product update timing decision, we will focus on the customer’s adoption decision and the role that the customer’s objectives play in the timing of releasing new innovations into the market.

Morgan et al. (2001), Krankel et al. (2006), and Wilhelm and Xu (2002) directly extended the work by Wilson and Norton (1989), investigating the introduction timing of multiple product generations. Using a discrete optimization approach, Morgan et al. (2001) studied the time-quality tradeoff facing a firm that introduces product generations as technology evolves. They found that there is a significant difference in the introduction strategy for single generation products versus multiple generation products. Specifically, they concluded that it is often best to utilize a more rapid generation introduction, corresponding to
smaller improvements in product "quality", i.e., less innovation in more frequent generation releases.

While Morgan et al. modeled the development time and costs directly, Krankel et al. (2006) considered a stochastic arrival of incremental technology improvements and the diffusion of a durable consumer good in a market in their analysis of optimal introduction timing for "successive" generations of a product. They found a "state-dependent threshold policy" for the product release timing decision, which depended upon the cumulative sales and the difference between the technology on the market and the available technology for future upgrades. Wilhelm and Xu (2002) offered a model to be used as a decision support mechanism, in order to simultaneously address the product update timing, production levels, and pricing decisions. Using a stochastic dynamic programming approach, their formulation maximized expected profit while considering uncertainties such as supplier lead times and manufacturing setup times for the new product generation. Although Wilhelm and Xu incorporated a supply chain perspective within their new product generation timing model, they did not directly address the customer’s viewpoint.

Although the Krankel et al. investigation is one of the first to address both diffusion and product innovations, it is limited to the introduction of durable goods constant prices in a monopoly, and it "does not consider the effects of introduction timing on consumers’ purchase strategies and resulting demand patterns." Morgan et al. (2001) also acknowledged the limitation of their approach, which does not incorporate the "consumer appetite for new products". It is in this area, regarding the relationship between generation introduction timing and the physician’s adoption strategies that this study contributes to the literature.

Most recently, the product introduction timing decision has been studied by Li and Jin (2009), Druehl et al. (2009), and Arslan et al. (2009). While Li and Jin studied the product introduction timing decision in a market with evolving technology, concentrating on an incumbent firm and entrant firm scenario, the investigation presented by Druehl et al., tackling a firm's optimal product update pace considering diffusion, is more applicable to this research. They incorporated a variety of product development and product diffusion aspects into their model which previous authors, such as Wilson and Norton (1989), Morgan et al. (2001), and Krankel et al. (2006), addressed separately. However, unlike Druehl et al., who assumed a solo product rollover policy, Arslan et al. (2009) considered two rollover scenarios in their investigation of both the timing of a new product generation’s entry into the market, as well as its pricing. The Druehl et al. findings indicated that the Bass (1969) product diffusion parameters play a significant role in the optimal product update pace. For future extensions, the authors suggested that the "game-theoretic nature" of the firm-customer relationship be considered, or incorporate the customer’s decision whether to purchase immediately or wait for a model update. As pointed out, "such a model would also
include product quality as a decision variable, while here we limit ourselves to deciding only pace.“ This work addresses product quality indirectly, by assuming that product quality (i.e., clinical value) is directly proportional to the update pace.

With the inclusion of both the customer (physician's) adoption decision and the product innovation decision, this study extends earlier studies on product update pace. The customer (physician) adoption decision process is handled directly within the applied method, and it is driven by the physician's own objectives. Furthermore, while some authors, including Souza (2004), have suggested manufacturer learning plays a role in product update timing, to the author's best knowledge, no published research incorporates learning curves on the consumer (physician) side of the product introduction timing literature. All of the models reviewed here have based the optimal product update timing decision upon the manufacturer's development, production, or other costs. As these authors have found, cost has a significant effect on the most profitable pace. Unlike these preceding works, we exclude the role of costs to concentrate on the revenue-generating impact that the product update pace has upon the manufacturer, within the unique structure of the PPI supply chain.

2.2 Product Rollover Decisions

Related to the product update timing decisions discussed above is a firm's decision to phase out earlier product versions. Billington et al. (1998) pointed out that, “To manage product rollovers efficiently, it is critical to plan the introduction of new products and the displacement of old products jointly. Most of the literature treats the two processes separately.” As suggested by Billington et al., this investigation incorporates the manufacturer's decision to halt sales of the previous product version within the PPI supply chain model. Erhun et al. (2007) also recommended strategies for managing product transitions, including the analysis of supply and demand risks, sharing information across the firm's functional areas, and understanding the “interplay” between product generations. Their empirical work on product transitions at Intel, conducted between 2001 and 2004, highlighted the importance of both the product update timing and product rollover decisions.

The work by Lim and Tang (2006) and Li and Gao (2008) provide examples of applying a quantitative modeling approach to product rollover decisions. Lim and Tang (2006) presented a model which addressed the optimality of single versus dual product rollover, as defined by Billington et al., as well as the optimal prices and timing for the rollover to take place. They found that in the single rollover scenario, as the price sensitivity increases and the demand for the new product is higher than the demand for the old product, the profits from the new product are less than the profits from the old product, therefore the new product version timing is delayed. They also found that a dual-product rollover strategy is only
optimal if, during the time period when both product versions are available, the firm’s profit is sufficiently large. Lim and Tang’s approach did not incorporate demand, cost or product development time uncertainty. It also neglected inventory costs and supply chain management aspects of the product price, introduction time, and product rollover decisions. However, they provided an important first look into an analytical method for understanding these decisions in concert. As with the approach offered by Lim and Tang, this work addresses the introduction timing and the product rollover timing simultaneously; however, given the unique PPI supply chain scenario, price sensitivity is not a primary concern for the adopters.

Li and Gao (2008) analyzed product rollover decisions from a different perspective. Assuming a solo-roll strategy, as defined by Billington et al. (1998), they investigated the effects upon a periodic-review inventory system when a manufacturer decides to either disclose or hide information about new product generation timing with downstream supply chain members. They found that sharing information is always in the best interest of both the manufacturer and the retailer, when the supply chain inventory is coordinated. Like Li and Gao, this work accounts for other supply chain members when addressing product rollover decisions; however, the information sharing focus they offered is not included. Research investigating product rollover decisions in conjunction with new product generation timing decisions is limited. This study contributes to this growing research area.

2.3 Relationship Marketing Decisions

As observed by Crosby et al. (1990), “Salespeople involved in the marketing of complex services often perform the role of ‘relationship manager’. It is, in part the quality of the relationship between the salesperson and the customer that determines the probability of continued interchanges between those parties in the future.” To gain further insights into this phenomenon, they completed an empirical study which indicates that the relationships between a firm’s sales rep and its customers are predictors of the future successes from the relationship. Further, the sales rep in a high quality relationship is able to provide “assurance” to the customer, who experiences uncertainty due to the complexity of the service being provided. This work quantitatively models the effects of a similar relationship which commonly occurs between a PPI manufacturer’s sales rep and physicians.

Within the healthcare context, some literature exists on the relationships between physicians and sales reps. Wright and Lundstrom (2004) presented a set of characteristics to describe a sales rep-physician relationship developed for the purpose of selling pharmaceuticals. They theorize that these characteristics are used by physicians to form perceptions of the sales reps. However, these concepts were not tested empirically or analytically. Trombetta (2007) highlighted the current issues of the PPI supply chain, specifically, and suggests that PPI and other medical device manufacturers develop
service-oriented relationships with hospitals. He offered as an example the General Electric (GE) approach to selling magnetic resonance imaging (MRI) equipment as an ongoing service versus a one-time equipment purchase. Although there is minimal literature within the healthcare context, given recent controversies regarding the relationships between some PPI manufacturers and physicians (Wilson et al. 2008), it is likely that more relationship management work will soon follow.

Outside the context of the healthcare industry, many volumes of literature exist on the subject of relationship marketing. Several discussions on the evolution of work in this area are available, including Sheth and Parvatiyar (1995), Eiriz and Wilson (2006), and Rust and Chung (2006). Rust and Chung (2006) focused upon relationship marketing within service industries, and their work included a less commonly discussed perspective on related quantitative models.

Additionally, an excellent summary of existing quantitative work on a firm’s relationship marketing investment decisions is presented by Musalem and Joshi (2009). Some other recent examples of quantitative models regarding relationship marketing include Rust et al. (2001), Netzer et al. (2008), and Khan et al. (2009). While these efforts focus upon understanding a customer’s value, how relationships change dynamically over time, and the value of individual-level marketing, respectively, this investigation seeks to understand the effects of relationship marketing upon customer learning, as well as product development decisions.

In line with Musalem and Joshi (2009), this study utilizes a game-theoretic approach in order to capture the strategic interaction between the manufacturer and customer (physician), with the inclusion of the sales rep. Other authors have recognized the potential of applying game theory concepts within the broad relationship marketing arena. Hogan et al. (2002) suggested that, along with other quantitative methods, game theory could be used to capture the “dynamic nature” of customer relationships.

It has been observed that PPI manufacturers rely upon their physician relationships during their new product development efforts (Burns 2002). However, to date, no work that quantitatively models the effects of relationship marketing upon the pacing of new product generations has been found. Further, the impact of its use as a training mechanism for complex products has not been located within the extant literature. By modeling the manufacturer’s use of a sales rep to assist physicians with new product generation adoptions, this work contributes to this connection between relationship marketing and new product development.
2.4 Hospital PPI Cost Control Policy

The existing literature regarding PPI cost control efforts for hospitals is limited to case studies and trade publications. As described previously, multiple PPI cost control strategies have been suggested in trade publications. All of the common methods reported within the trade publications support one or both of the following two objectives: (1) to reduce the number of PPI brands purchased, in order to gain volume discounts, and (2) to influence physicians to consider price when determining their preference for a PPI.

Product standardization, or the “formulary” approach, described by Montgomery and Schneller (2007), is a strategy in which the hospital restricts its physicians’ choice of vendors. In contrast, the price ceiling method, mentioned by Robinson (2008), allows physicians to select any PPI they prefer that is priced at or under the ceiling. While the formulary approach aims to gain volume discounts, and the price ceiling method increases physicians’ awareness of price, neither utilizes a collaborative strategy with the physicians.

Another approach, which makes in-roads for both the quantity discount and price awareness objectives, is some form of physician-based assessment committee in which physicians collaborate in order to whittle down their collective preferences. Different versions of this collaborative cost control approach, sometimes referred to as value analysis teams, are described by Schneller and Smeltzer (2006), Wilson et al. (2008), Robinson (2008), and Joshi (2008). Hubmayr (2001) presented an implementation of this method at Mayo Clinic, who instituted a committee to combat the high variance they were paying for the same stents and orthopedic implants at different locations. The committee collaborated with physicians at each location to select a small number of devices from the most-preferred manufacturers. Mayo also incorporates a “technology clause” into all PPI purchasing contracts in order to ensure that the most innovative products are available to them.

Gainsharing concepts, in which hospitals share PPI savings with physicians, are new to the arena (Ketcham & Furukawa 2008; Wilson et al. 2008). Gainsharing has been approved only on a limited basis by the FDA, and it has generated controversy because some believe it creates a conflict of interest for physicians (MacVaugh 2005).

Burns et al. (2009) indicated that although hospitals have attempted many strategies, there is a lack of data indicating the effectiveness of any of these approaches. Based upon a variety of industry sources, they also assert that, despite these measures, hospitals have less influence upon the physicians than the manufacturers. In lieu of a large-scale data collection effort to understand the effectiveness of the many possible cost containment policies, this study addresses this gap by utilizing a game-theoretic approach to understand how hospitals may be able to influence the physicians’ adoption time of new PPI product generations.
3. Methodology

3.1 Problem Formulation

3.1.1 Nature of the Manufacturer-Physician Relationship

In an industry where innovations and product quality are of primary importance, the PPI manufacturer produces a product line with a time-pacing, or “train schedule”, strategy. This allows the manufacturer to provide the physician with successive generations of an evolving product at a constant pace, which eases the coordination of internal product development processes (Eisenhardt & Brown 1998; Christensen 1997). Given this scenario, the manufacturer must decide how frequently to release a new generation. Once in the market, a product generation's popularity follows a typical lifecycle curve, which rises and falls to indicate the volume of sales or customers over time. Product adoption curves, recognized as S-shaped (Rogers, 2003), may be truncated by the manufacturer's decision to phase out the previous generations of a product. This decision, sometimes referred to as the “product rollover policy”, can be categorized into two main types of strategies, the solo-product roll and the dual-product roll (Billington et al., 1998). Dual-product roll strategies permit the new product generation and the earlier product generation to be on the market at the same time. Several studies which model the product update pace decision quantitatively assume a solo-product roll within their formulation (Li & Jin 2009; Carrillo 2005; Souza et al. 2004, Krankel et al. 2006), but we consider the more general scenario of up to two product generations offered by the manufacturer simultaneously, in line with Druehl et al. (2009). Billington et al. (1998) claimed that successful dual-product rolls have “efficient coordination and flexibility in the manufacturing, distribution, and marketing of both the old and new product.” The time-pacing approach has been recognized as a method of achieving this type of coordination and efficiency for product development activities (Christensen 1997; Eisenhardt & Brown 1998). Therefore, we consider the manufacturer’s time pace decision and rollover policy decision simultaneously.

When new product generations have a higher per-unit profit than earlier generations, early adoption is in a manufacturer's best interest. Diffusion of a product generation into the market is indicated by an upward slope in the lifecycle curve. The manufacturer incorporates new features in order to encourage physicians to upgrade to the newest, most expensive generation more quickly. As with the Medtronic case described by Christensen (1997), PPI manufacturers have an excess of potential product features to incorporate into each new product generation. Therefore, it is reasonable to assume that the clinical value of a new product generation increases as the time between successive product generations increases.
Adoption Decision

When a PPI manufacturer releases a new product generation, physicians must decide whether to adopt the new generation, remain with the current generation, or switch brands. The medical community’s estimate of a product generation’s clinical improvement directly influences a physician’s decision. It is common for physicians to be somewhat loyal to their preferred manufacturer, as described previously. The timing and outcome of a physician’s adoption decision affects the shape of the lifecycle curve for each generation. Prior to adopting a new product generation, the average physician requires some evaluation time to learn about the new generation’s existence and enhancements in order to make an adoption decision. Rogers (2003) describes this evaluation time as the "innovation-decision period". During this innovation-decision period, the physician acquires knowledge of the new product generation from peers. Peer learning could take place via multiple mechanisms, which is evident in the research completed by Pisano et al. (2001). They studied the effects of organizational learning upon physician adopters of a new minimally invasive cardiac surgery. They studied different hospital cultures and presented two extreme examples: one organization with high levels of cross-department communication, teamwork, and engagement from the adopting physician. Additionally, team members involved in the new procedures worked to develop an understanding of not only their roles, but the roles of other team members as well. In contrast, another hospital had multiple technology adopters, little team stability, a lack of inter-departmental communication efforts, and a low level of team engagement. Pisano et al. (2001) found that the learning curve slope for procedures performed at these two organizations were very different, suggesting that organizational communication and learning play a large role in improving clinical results through experience.

Rogers (2003) grouped adopters into five categories (i.e., a discrete probability distribution): innovators (2.5%), early adopters (13.5%), early majority (34%), late majority (34%), and laggards (16%). For a detailed description of the common values that individuals within each category share, refer to Rogers (2003). In line with this fundamental finding within the diffusion of innovations literature, this research is built upon the concept that a given physician may elect to adopt a new product generation earlier or later than his counterparts, such that the adoption time of the average physician can be represented by a random variable.

A physician’s clinical results are affected by his **product adoption decision** due to both the PPI features and his experience with the adopted generation, which is indirectly driven by patient demand. Learning curve theory indicates that a physician’s results will improve with more experience (i.e., more patients). In a study investigating the effects of organizational learning versus individual learning for physicians performing minimally invasive cardiac surgery, Pisano et al. (2001) state that, “An extensive number of empirical studies have documented the link between cumulative experience (e.g., cumulative production volume, cumulative production time) and some measure of operational performance improvement (e.g.,
cost reduction, yield improvement, productivity improvement). Within the PPI supply chain, we assume that when a physician adopts a product generation, he must progress through a learning curve before achieving the maximum clinical effectiveness and productivity that is possible with the new product generation. With each procedure performed, the physician’s experience with the adopted generation grows, and his effectiveness and productivity improve, approaching the maximum clinical results achievable with the adopted generation. The amount of experience that a physician can obtain, measured by the number of procedures performed using a product generation, is limited by the demand within his patient population for the PPI and its associated procedure.

The decisions and parameters described above provide a foundation for understanding the unique characteristics of the PPI manufacturer-physician relationship and are represented in the PPI supply chain influence diagram shown in Figure 1. This diagram follows conventions introduced by Shachter (1986), in which rectangular nodes represent decisions, or actions. Circular nodes represent “chance nodes” or sources of uncertainty, and rounded rectangles, or “value nodes”, indicate the chance nodes that are outcomes of interest, or the supply chain players’ objectives. Arcs entering (or exiting) decision nodes indicate “informational arcs”, and arcs entering chance nodes are “conditional arcs” which “represent probabilistic dependence”. Notation and development of the model utilizing the nodes shown in Figure 1 is discussed in Section 3.3.1.

Figure 1: Manufacturer-Physician Influence Diagram
3.1.2 Incorporating the Manufacturer's Sales Representative

It is common for a PPI manufacturer to employ a sales representative, or “sales rep”, to manage relationships with physicians. This complexity is layered into the original physician-manufacturer game to further analyze the impact of the manufacturer’s sales representative upon the physician’s adoption decision and the manufacturer’s own product update pace. The addition of training from the sales representative within the PPI supply chain model, results in the modified influence diagram shown in Figure 2. The sales rep (represented by the Training Factor node) provides a means for the manufacturer to reduce the time required for a physician to progress through the assessment period or accelerate the physician’s learning curve after adopting a new product generation. Additionally, by building a long-term relationship with a physician through a sales rep, the manufacturer is able to influence physician loyalty.

Figure 2: Manufacturer-Physician Influence Diagram with Sales Rep

3.1.3 Hospital Cost Control

A hospital can implement policies to limit a physician's adoption of new product generations. For example, a hospital may require that the cost per unit of a PPI is below a given level. This policy is modeled as a
price cap decision in this work. The hospital’s cost control policy, and its influence on the PPI supply chain, is shown in Figure 3.

The hospital’s price cap decision influences two key elements of the three-player supply chain model. First, the price cap decision affects the physician’s adoption decision by limiting the adoption of PPIs priced higher than the cap. In addition to having an influence on the physician’s adoption decision, the hospital cost control policy impacts the volume of the PPI procedures performed at its facility. This is because when a hospital's cost control policy contradicts the physician's adoption decision, the physician may elect to admit some percentage of his patients to another hospital. This decision allows physicians to gain experience with the new product generation and provide the diverted patients with a better version of the product. However, a price cap will reduce the volume of procedures at the hospital. A manufacturer is not adversely affected by a loss in volume at a specific hospital due to the compensation from diverted patients.

These additional parameters within the PPI supply chain model are depicted in the influence diagram shown in Figure 3.
3.1.4 Assumptions

This study incorporates the following assumptions:

- The price of a new product generation is greater than the price of the previous product generation.
- If a physician’s preferred adoption time occurs after the rollover period, then the physician will maintain current clinical results by switching to another manufacturer.
- The overlap in availability between two subsequent product generations from a manufacturer is greater than zero.
- When a physician adopts a new product generation, he must progress through a learning curve before achieving the maximum clinical effectiveness and/or productivity that is possible with the new product generation.
- A physician can learn from his peers prior to adopting a new PPI generation in order to improve his initial clinical results with the new generation.
- The clinical value of a new product generation increases as the time pace increases between successive product generations.
- Constant demand is assumed for a PPI (i.e., decisions within the PPI supply chain model, including those determined by the physician, will not induce higher demand for a PPI and its associated procedure).
- A manufacturer, physician, and hospital will each behave rationally in order to maximize their objectives, and are concerned only for their own best interests.
- The manufacturer, physician, and hospital must select their strategies without any knowledge of the strategies of the other players.
- The manufacturer and physician do not account for future interactions with each other while making their decisions.
- The payoff for the manufacturer’s sales representative is not separable from the manufacturer’s objective. In other words, the sales rep does not behave strategically or engage in a separate decision-making process.

3.2 Method

The PPI manufacturer, physician, and hospital each have objectives that are functions of decisions made by not only themselves, but each other. In order to capture the interdependencies between these players’ decisions, this research uses a game-theoretic approach. Game theory is defined by Osborne and Rubinstein (1994) as “a bag of analytical tools designed to help us understand the phenomena that we observe when decision-makers interact.” Game theory supports analytical models that consider uncertainty, multiple decision makers with differing objectives, and decision timing. Section 3.2.1 reviews
concepts and terms of game theory that are used to define the strategic interaction of PPI decision-makers. The nature of the PPI supply chain game is described in Section 3.2.2. This is followed by an application of a game-theoretic approach in Section 3.3, which mathematically defines the three game variations described in Section 3.1. Finally, Section 3.4 summarizes the experiments performed based upon the game-theoretic formulations.

3.2.1 Terminology

Within a game-theoretic approach, decision-makers are commonly called players, and a game describes player interaction (Osborne & Rubinstein 1994). A fundamental assumption underlying the game-theoretic approach is rationality on the part of players. Rationality implies that a player is, “aware of his alternatives, forms expectations about any unknowns, has clear preferences, and chooses his action deliberately after some process of optimization” (Osborne & Rubinstein 1994). Rational players formulate a strategy, or a “complete plan of action” (Gibbons 1992). A player’s strategy is based upon his knowledge of the game, but players may be uncertain of their knowledge. A player’s set of possible strategies is termed the strategy space, and the set of possible actions is the action space (Gibbons 1992). A game’s solution predicts the strategies that will result from the interaction of rational players, along with the players’ payoffs that result from the predicted strategies.

The game theory literature includes a large variety of games that vary according to the rules of the game. Games can be classified by many features, including such characteristics as the number of players, the timing of the players’ decisions, whether and how uncertainty is addressed, and the degree of player cooperation.

Number of Players

Games representing the three scenarios described in Section 3.1 have players corresponding to the decision makers. To assess how the physician’s learning and the manufacturer’s sales representative affect the manufacturer’s product update pace, only two players, the physician and the manufacturer, need to be modeled. To investigate the third scenario, where the hospital selects a PPI cost control policy, the game must be expanded into a three-player scenario.

Player Payoffs

The relationships between player payoffs offer another characteristic for distinguishing between types of games. In any game, each player desires to maximize or minimize his utility of a resource. This utility is a payoff that players receive at the game’s conclusion, and it is a function of the strategies selected by themselves, as well as other players. For example, in the PPI supply chain, the physician, manufacturer, and hospital strive to maximize (or minimize) their objectives of clinical outcomes, product diffusion, and cost, respectively. Each of these objectives is affected by how long the physician spends assessing the
product prior to making his adoption decision. In this sense, the players are competing for time. In zero-sum games, the sum of all players' payoffs equals zero. In other words, "one player's gain is another player's loss," (Webster 2008). As this is not the case within the PPI supply chain, a non-zero-sum game must be used to model the relationships between the physician, manufacturer, and hospital.

**Player Actions**

Depending upon the nature of the timing of players' decisions, a game may be described as being either static or dynamic (Gibbons 1992). Static, also referred to as "normal form" (Gibbons 1992) or "strategic" (Osborne & Rubinstein 1994), describes a game in which players are unaware of each other's strategies until after a strategy has been selected. In a dynamic game, also known as the "extensive form" (Gibbons 1992), players can make decisions according to some sequence and each player is aware of the results from previous moves by other players (Webster 2008). To understand the basic interactions between the manufacturer and the physician, we utilize a static game, in which neither player communicates upcoming decisions to other players. Within the PPI industries, manufacturers compete on innovation, so it is reasonable to assume that the selected product update pace and rollover policy would be private information. Likewise, it is doubtful that the manufacturer will have knowledge of the average physician's adoption time prior to the release of a new product generation. Therefore, when considering the timing of player actions, a static game is reasonable.

**Timing of Player Actions**

The concept of static and dynamic games explains the timing of decisions which occur before the players receive their payoff. However, if the same set of moves occurs multiple times, resulting in payoffs with each repetition, then a game is referred to as a repeated game. Osborne and Rubinstein (1994) provide an excellent description of the benefit of using a repeated game: "The model of a repeated game is designed to examine the logic of long-term interaction. It captures the idea that a player will take into account the effect of his current behavior on the other players' future behavior, and aims to explain phenomena like cooperation, revenge, and threats." If these long-term behaviors are of interest, games may be constructed to be either finitely repeated or infinitely repeated.

The selection of either a finite or infinite horizon can have significant effects upon the model's outcome, so it is necessary to consider which scenario most accurately reflects the modeled system (Osborne & Rubinstein 1994). Rubinstein (1991) provides an intuitive explanation of the finite or infinite game decision that is faced when modeling a repeating game, pointing to Aumann (1959), who, in reference to the infeasibility of infinite plays in the real world, stated that, "nobody really expects an infinite number of plays to take place; on the other hand, after each play we do expect that there will be more." Otherwise, if repetition is not in the nature of the system behavior, a one-time game can be applied.
It is possible to view the PPI supply chain product update game as a repeated game, in which the manufacturer’s product rollover policy, the physician’s adoption and time-to-assess decisions, and the hospital’s cost control policy, are all repeated for every product generation that is released. However, in accordance with the time-pacing policy, which necessitates that a product update pace is selected and maintained over the long-haul, the manufacturer’s product update pace decision is made only once during a game. Future research could consider a repeated game in which the manufacturer reselects its product update timing with each iteration of the game. When assuming that the manufacturer and physician do not account for future interactions with each other while making their product update game decisions, it is appropriate to select an unrepeated game. In a static, unrepeated game, each PPI supply chain player is not aware of the others’ moves when they select their strategies.

**Handling Uncertainty**

In many instances, it is important for the game to address uncertainty within the system. One method of incorporating uncertainty into a game-theoretic approach is to utilize a stochastic game. Mertens (2002) and Sorin (2003) describe stochastic games as repeated games that have a “state of nature.” In each repetition, this external state changes with some probability. While the stochastic game gives a method for incorporating exogenous changes into the model, reflecting the players’ uncertainty of future system parameters, it is constructed upon the premise that the game’s current state is observable to the players (Mertens 2002). Stochastic games present a useful approach for many situations, representing the uncertainty in the PPI supply chain with this approach presents a difficulty. Handling many of the uncertain parameters with the concept of a state would be useful. However, unlike the structure of a typical stochastic game, the players in the PPI supply chain are always unsure of certain parameters, i.e., the current state is not entirely known by any player. Therefore, selecting actions based upon the “state of nature” is not appropriate. Should it become necessary to model uncertainty, the concept of incomplete information will be useful.

Game theory models necessitate that all parameters within the model are known by all players before any strategies are selected. This is also known as *complete information*. While this construct appears inflexible, Harsanyi (1967) developed a mechanism for representing the effects of *incomplete information* by introducing the concept of player types and beliefs. When applying this mechanism, an additional player, Nature, selects player types for the other players, and shares the type privately with each player prior to selection of a strategy. This is termed a Bayesian game, or a game with incomplete information. However, while many parameters within the PPI supply chain can be viewed as uncertain, these parameters are equally uncertain to all players, and no player has private information that reduces their uncertainty of these parameters. For example, the clinical value of a new product generation could be viewed as a random variable, but neither the manufacturer, nor a physician, has any private knowledge of
how well the product’s new attributes will assist the patient in the long term. In this sense, both players have equivalent knowledge of each other’s payoff function, or complete information.

Following the discussion of game characteristics above, the core relationship between the manufacturer and physician, as depicted in Figure 1, can be formulated as a two-player, non-zero sum, static, unrepeated game with complete information. This is also known as a static or strategic game with complete information (Gibbons 1992; Osborne & Rubinstein 1994).

3.2.2 Static Game with Complete Information

In a static game with complete information, players receive a payoff corresponding to the actions that all players selected. Knowing that each player desires to maximize (or minimize) his or her payoffs, each player selects an action that accounts for what the other players will want to do (Gibbons 1992; Osborne & Rubinstein 1994).

Solution Concepts

A solution to a game will indicate which actions will be taken by all players in the game, in addition to what each player’s expected payoff will be at the end of the game. The Nash equilibrium is the “most commonly used solution concept in game theory,” (Osborne & Rubinstein 1994). A Nash equilibrium occurs when, “each person’s strategy is a best response to the strategies chosen by the other players,” (Campbell 2006). A player’s best response is a strategy that results in the highest payoff for a player, given the other players’ strategies (Campbell 2006). Dominant strategy equilibrium is a special case of a Nash equilibrium, in which all players have a dominant strategy that will maximize their payoffs no matter what strategy is selected by every other player (Campbell 2006).

To illustrate the concepts of Nash equilibrium and dominant strategy equilibrium, we present the following two-player example game: Player 1 and Player 2 must select from actions A, B, and C. If Player 1 selects B and Player 2 selects A, then their payoffs will be 4 and 2, respectively. The remainder of the payoff information is presented in the bimatrix below (Table 1), which is the normal form representation of a static game with complete information.

Table 1: Normal Form of Example Game

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Player 1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>3, 1</td>
<td>2, 4</td>
<td>1, 5</td>
</tr>
<tr>
<td>B</td>
<td>4, 2</td>
<td>3, 1</td>
<td>2, 4</td>
</tr>
<tr>
<td>C</td>
<td>5, 1</td>
<td>4, 2</td>
<td>3, 3</td>
</tr>
</tbody>
</table>
In this example, no matter what action Player 2 selects, it is always best for Player 1 to select action C. Likewise, no matter what action Player 1 selects, it is always best for Player 2 to select action C. Therefore, the strategy combination (C, C) is a dominant strategy equilibrium, and a Nash equilibrium, for the example game. The expected payoff for both players is 3.

No Pure Strategy Solution
A Nash equilibrium is classified as a pure strategy equilibrium, because it is comprised of a single strategy for each player. Nash also defined the concept of a mixed strategy equilibrium, which consists of a probability distribution that describes the likelihood for each player to select each strategy (Gibbons 1992). Occasionally, a game may result in only mixed strategy equilibrium, and no pure strategy equilibrium, as in the game Matching Pennies (Gibbons 1992). In this game, each player decides whether to place a penny on a table with the heads up or down. If both players place the penny in the same position (“matching pennies”), then Player 2 wins. However, if the pennies do not match, then Player 1 wins. The winner receives his opponent’s penny. The normal form of Matching Pennies is given in Table 2.

Table 2: Normal Form of Matching Pennies

<table>
<thead>
<tr>
<th></th>
<th>Heads</th>
<th>Tails</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heads</td>
<td>-1, 1</td>
<td>1, -1</td>
</tr>
<tr>
<td>Tails</td>
<td>1, -1</td>
<td>-1, 1</td>
</tr>
</tbody>
</table>

From Table 2, we see that if Player 1 were to place the penny heads up, then Player 2 would elect to also place a penny heads up. However, if Player 1 elects tails up, Player 2 would have a different strategy. In this situation, there is no pure strategy Nash equilibrium. As Gibbons (1992) describes, “In any game in which each player would like to outguess the other(s), there is no Nash equilibrium...because the solution to such a game necessarily involves uncertainty about what the players will do.” In these cases, one or more mixed strategy Nash equilibria will be present. In this work, a negligible number of trials resulted in no pure strategy equilibrium. Therefore, conclusions here are drawn from only pure strategy equilibrium outcomes.

Multiple Pure Strategy Solutions
The simple example presented in Table 1 results in a single pure Nash equilibrium. However, it is quite possible for multiple Nash equilibria to result from a similar game. For example, in the classical Stag Hunt Game, introduced by the French philosopher Jean Jacques Rousseau, two pure equilibria exist with only four possible outcomes (Skyrms 2004; Shor 2005). This game depicts a scenario in which two people must select a strategy to hunt for their sustenance. Each person can select to either hunt a rabbit or hunt...
a stag. A player is able to capture a rabbit individually, but for either player to be successful in a stag hunt, both players must work together. A normal form example of the Stag Hunt is shown in Table 3.

Table 3: Stag Hunt Game

<table>
<thead>
<tr>
<th>Hunter 1</th>
<th>Stag</th>
<th>Rabbit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hunter 2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stag</td>
<td>10, 10</td>
<td>0, 8</td>
</tr>
<tr>
<td>Rabbit</td>
<td>8, 0</td>
<td>5, 5</td>
</tr>
</tbody>
</table>

In this game, the pure Nash equilibria occur at (Stag, Stag) and (Rabbit, Rabbit). This example demonstrates how the relationships between the players' payoffs dictate whether multiple equilibria are present in a bimatrix. Due to the size of the manufacturer and physician action spaces, and the complexity of the payoff function definitions, it would not be surprising for multiple equilibria to be present in some instances. Therefore, in the following section, we define an approach for handling the presence of multiple equilibria.

Given the two equilibria (Stag, Stag) and (Rabbit, Rabbit) in the Stag Hunt Game, a natural question arises: Which of these two outcomes would we expect to see? Many authors, including Harsanyi and Selten (1988), Cooper et al. (1990), and Myerson (1991), recognize the difficulties that arise when attempting to predict behavior for a game which has multiple equilibria. Myerson (1991) summarizes several concepts that can address the occurrence of multiple pure Nash equilibria. One approach uses the concept of Pareto dominance. A Nash equilibrium is Pareto dominant, or Pareto efficient, if there are no other equilibria in which a player is better off. Goldberg proposed a non-dominated sorting algorithm (1989), also called Pareto ranking by Baeck, Fogel, and Michalewicz (1997), which is a method for ranking multiple equilibria. This method is executed by finding the Pareto dominant equilibrium within the set of Nash equilibria, ranking it, and then removing it from the population and finding the Pareto dominant equilibrium of the remaining set. This process is repeated until all equilibria are ranked. The result is a ranking which orders the equilibria by the number of other equilibria in the original population that Pareto-dominate it (Goldberg 1989, Baeck, Fogel, and Michalewicz 1997). Applying the Pareto ranking for the game presented in Table 3 results in a ranking of 1, 2, for (Stag, Stag) and (Rabbit, Rabbit), respectively. This is because at the (Stag, Stag) equilibrium, at least one of the players (or in this case, both players) is better off than at the other equilibrium (Rabbit, Rabbit). It is possible for a game to result in two or more equilibria with equivalent Pareto efficiency. In these instances, these equilibria are assigned equal ranking.

The Pareto-ranking procedure can be applied to predict behavior within the PPI game construct without the introduction of additional parameters. Therefore, for cases in which multiple pure Nash equilibria occur, we utilize the Pareto-ranking approach to make basic predictions regarding the players' behaviors.
3.3 Formulation

In this section, we introduce the basic structure and notation used to model three static games with complete information. General notation that is used throughout all games is summarized in Table 4. Additional notation for each game is introduced in each of the subsequent subsections.

Table 4: General Notation

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>General game notation</td>
<td>$\Gamma = 1, II, \text{ or III}$</td>
<td>Game</td>
</tr>
<tr>
<td></td>
<td>$N$</td>
<td>Number of players</td>
</tr>
<tr>
<td></td>
<td>$i = 1, \ldots, N$</td>
<td>Index of players</td>
</tr>
<tr>
<td></td>
<td>$A_i$</td>
<td>Player i’s action space</td>
</tr>
<tr>
<td></td>
<td>$u_{i,\Gamma}$</td>
<td>Player i’s payoff function in game $\Gamma$</td>
</tr>
<tr>
<td>Player decisions</td>
<td>$\theta$</td>
<td>Product update interval, in months (manufacturer’s decision)</td>
</tr>
<tr>
<td></td>
<td>$\rho$</td>
<td>Rollover policy, in months (manufacturer’s decision)</td>
</tr>
<tr>
<td></td>
<td>$\omega$</td>
<td>Adoption time, in months (physician’s decision)</td>
</tr>
</tbody>
</table>

3.3.1 Manufacturer-Physician Model and Notation

In this section, we introduce the basic structure and notation used to model the two-player static game with complete information, in which the manufacturer and the average physician compete for the utility of adoption time. The notation used to represent the Manufacturer-Physician static game is summarized in Table 5.

3.3.1.1 Players

There are two players, the manufacturer ($i = 1$) and the average physician ($i = 2$). The manufacturer plays to maximize revenue, which is accomplished by maximizing the revenue generated by the latest generation of a PPI product. The physician player represents the average physician, who behaves rationally in order to maximize clinical results. The term “clinical results” implies many different metrics which the medical community can use to measure the success of a physician, such as patient recovery time, mortality, and time in the operating room. Because the relative importance of these different metrics is dependent upon the procedure at hand, we generalize by using the term “clinical results” to represent a physician’s motivation to perform well clinically.

3.3.1.2 Actions

The manufacturer’s action space, $A_1$, is described by possible values for the product update interval ($\theta$), and the rollover policy ($\rho$). The product update interval is defined to be the time between arrival of
successive product generations to the market, and can be thought of as the inverse of the product update pace. The rollover policy is defined the time that the current product remains on the market following the introduction of the latest product generation. These values are calculated relative to the introduction of the latest product generation, which occurs at time zero.

The action space for the average physician, $A_2$, includes all possible values for $\omega$, the time at which the average physician prefers to adopt the new product generation.

Table 5: Physician-Manufacturer Model Notation

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adoption time distribution for physician population</td>
<td>$\tau$</td>
<td>Continuous random variable representing preferred adoption time</td>
</tr>
<tr>
<td></td>
<td>$\lambda_1$</td>
<td>Shape parameter for adoption time distribution</td>
</tr>
<tr>
<td></td>
<td>$\lambda_2(\rho, \omega, \lambda_1)$</td>
<td>Shape parameter for adoption time distribution</td>
</tr>
<tr>
<td></td>
<td>$\omega_{\min} - 1$</td>
<td>Left endpoint for adoption time distribution</td>
</tr>
<tr>
<td></td>
<td>$\omega_{\max} + 1$</td>
<td>Right endpoint for adoption time distribution</td>
</tr>
<tr>
<td></td>
<td>$\rho_1$</td>
<td>Point at which $\rho$ effect on $\lambda_2(\rho, \omega, \lambda_1)$ begins to decrease</td>
</tr>
<tr>
<td></td>
<td>$\rho_2$</td>
<td>Point at which $\rho$ effect on $\lambda_2(\rho, \omega, \lambda_1)$ no longer decreases</td>
</tr>
<tr>
<td></td>
<td>$k$</td>
<td>Constant defining maximum value of $\lambda_2$</td>
</tr>
<tr>
<td>Probability of physician switching to another manufacturer</td>
<td>$S(\theta)$</td>
<td>Discrete random variable representing whether physician switches to another manufacturer or not, as a function of the product update interval ($\theta$)</td>
</tr>
<tr>
<td>Clinical value of new product features</td>
<td>$V(\theta)$</td>
<td>Clinical value of new product generation</td>
</tr>
<tr>
<td></td>
<td>$V(0)$</td>
<td>Clinical value of new product generation when $\theta = 0$ (i.e., equivalent to clinical value of previous generation)</td>
</tr>
<tr>
<td></td>
<td>$V(\theta_{\max})$</td>
<td>Clinical value of new product generation when $\theta = \theta_{\max}$</td>
</tr>
<tr>
<td>Physician’s clinical results</td>
<td>$t$</td>
<td>Time index (months)</td>
</tr>
<tr>
<td></td>
<td>$R(t)$</td>
<td>Physician’s clinical results over time</td>
</tr>
<tr>
<td></td>
<td>$R(0)$</td>
<td>Physician’s clinical results at time zero (equivalent to previous generation)</td>
</tr>
<tr>
<td></td>
<td>$t_1$</td>
<td>Defines maximum domain of first segment of piecewise $R(t)$ function</td>
</tr>
<tr>
<td></td>
<td>$t_2$</td>
<td>Defines maximum domain of second segment of piecewise $R(t)$ function</td>
</tr>
<tr>
<td></td>
<td>$t_3$</td>
<td>Defines maximum domain of third segment of piecewise $R(t)$ function</td>
</tr>
<tr>
<td></td>
<td>$x_1$</td>
<td>Binary variable indicating if $\omega$ occurs after original product generation is discontinued</td>
</tr>
<tr>
<td></td>
<td>$x_2$</td>
<td>Binary variable indicating if $\theta$ occurs before physician can complete learning curve</td>
</tr>
<tr>
<td></td>
<td>$D(0)$</td>
<td>Drop in clinical results at time zero (if $\omega = 0$)</td>
</tr>
<tr>
<td></td>
<td>$D(\omega)$</td>
<td>Drop in clinical results as a linear function of $\omega$</td>
</tr>
<tr>
<td></td>
<td>$q$</td>
<td>Constant defining slope between $\omega$ and $D$</td>
</tr>
<tr>
<td></td>
<td>$L$</td>
<td>Number of cases to be completed to realize $V(\theta)$</td>
</tr>
<tr>
<td></td>
<td>$P$</td>
<td>Physician’s demand (number of patients) for PPI</td>
</tr>
<tr>
<td></td>
<td>$b$</td>
<td>Shape parameter of learning curve</td>
</tr>
</tbody>
</table>
3.3.1.3 Manufacturer’s Payoff

We address solely the manufacturer’s desire to maximize revenue, although realistically, a manufacturer would wish to maximize profit. However, in order to focus directly upon the effects of product complexity and physician learning, revenue is utilized as the manufacturer’s objective. In the initial formulation of the PPI supply chain, the two components of revenue, price and quantity, are handled via proxies. The new product generation’s clinical value, \( V(\theta) \), is used as a proxy for price, and the probability of adopting within the rollover policy represents quantity. The manufacturer’s payoff is defined as

\[
u_{1,t} = \Pr(\tau \leq \rho) \left[ 1 - S(\theta) \right] V(\theta)
\]

where \( \tau \) is the adoption time and \( S(\theta) \) is the probability that the average physician will become disloyal to his preferred manufacturer.

The proposed payoff function incorporates aspects to model the effects of rollover policy upon adoption time, update interval upon the probability of switching, and update interval upon product value. Each of these components is defined in the following subsections.

**Effects of Rollover Policy Upon Adoption Time**

The first component of the manufacturer’s payoff function, \( u_{1,t} \), is the probability of the average physician adopting the new product generation prior to the discontinuation of the previous product generation. Due to its flexible shape and defined endpoints the generalized beta distribution is used to model the distribution of physician adoption times, \( \tau \) (Gupta & Nadarajah 2004). To mimic the S-shape that is widely applied to innovation adoption times within the literature, the shape parameters, \( \lambda_1 \) and \( \lambda_2(\rho, \omega, \lambda_1) \), are constrained to be greater than one. The distribution for \( \tau \) is given by

\[
\Pr(\tau < x) \sim \text{GeneralizedBeta} \left( \lambda_1, \lambda_2, \omega_{\min} - 1, \omega_{\max} + 1 \right) = \\
\int_{\omega_{\min} - 1}^{x} \frac{1}{\beta(\lambda_1, \lambda_2(\rho, \omega, \lambda_1))} \left( \frac{x - \omega_{\min} + 1}{\omega_{\max} + 1 - \omega_{\min} + 1} \right)^{\lambda_1-1} \left( 1 - \frac{x - \omega_{\min} + 1}{\omega_{\max} + 1 - \omega_{\min} + 1} \right)^{\lambda_2-1} dx.
\]

The endpoints, \( \omega_{\min} - 1 \) and \( \omega_{\max} + 1 \), are defined to encompass the entire range of the physician’s action space and therefore,

\[
\Pr(\tau < (\omega_{\min} - 1)) = 0
\]

and

\[
(3)
\]
While $\lambda_1$ is given, the second shape parameter, $\lambda_2(\rho, \omega, \lambda_1)$ is calculated as a function of the physician’s adoption time, $\omega$, the manufacturer’s rollover policy, $\rho$, and $\lambda_1$. In order to align the manufacturer’s payoff with the action selected by the average physician in the game, the relationship between $\lambda_1$ and $\lambda_2$ from the definition of the beta distribution mean, $E[\tau]$ (5). This relationship is represented mathematically by equating the expected value of the adoption time, $E[\tau]$, to the physician’s adoption time decision, $\omega$, and solving for $\lambda_2$ in terms of $\lambda_1$ and $\omega$ (6).

$$E[\tau] = \omega_{\text{min}} - 1 + (\omega_{\text{max}} + 1 - \omega_{\text{min}} + 1) \frac{\lambda_1}{\lambda_1 + \lambda_2}$$

(5)

$$\lambda_2 = \left(\frac{\omega_{\text{max}} + 1 - \omega_{\text{min}} + 1}{\omega - \omega_{\text{min}} + 1} - 1\right) \lambda_1$$

(6)

In conjunction with the relationship between $\lambda_2$ and $\omega$ given above, a simple piecewise linear function (Figure 4) is used to model the manufacturer’s ability to influence physician adoption time through the rollover policy. This relationship is in place so that as the rollover policy, $\rho$, is decreased, the physician population is influenced to adopt the new product generation earlier. The value of $\lambda_2$ given by (6) is the shape parameter used for a physician population which is unpressured by the manufacturer to adopt PPI updates early, when $\rho$ is greater than a given threshold, $\rho_2$. As the rollover policy, $\rho$, is decreased below
this threshold, the influence upon the physician population is increased, causing the average adoption time to shift to an earlier adoption, as shown in Figure 5. This effect increases as $\rho$ decreases until a second threshold is reached at $\rho = \rho_1$. At this point, the maximum effective level of influence is reached.

![Figure 5: Effect of Product Rollover upon Distribution Shape](image)

The parameters $\rho_1$, $\rho_2$, and $k$ define the slope and range of this effect of the rollover policy, $\rho$, upon the adoption time distribution shape. This linear relationship is combined with the definition provided in (6) and, as derived in Appendix C, is expressed mathematically as

$$
\lambda_2(\rho, \omega, \lambda_1) =
\begin{cases}
\frac{(\omega_{\max} - \omega_{\min})}{\omega - \omega_{\min} + 1} k\lambda_1, & \rho \leq \rho_1 \\
\frac{k\lambda_1 - \left( \frac{\omega_{\max} - \omega_{\min}}{\omega - \omega_{\min} + 1} \right) \lambda_1}{\rho_1 - \rho_2} \left( \rho - \rho_1 \right) + \left( \frac{\omega_{\max} - \omega_{\min}}{\omega - \omega_{\min} + 1} \right) k\lambda_1, & \rho_1 < \rho < \rho_2 \\
\left( \frac{\omega_{\max} - \omega_{\min}}{\omega - \omega_{\min} + 1} \right) \lambda_1, & \rho_2 \leq \rho
\end{cases}
$$

(7)
Effects of the Update Interval upon the Probability of Switching

Following the calculation of the adoption time probability density function, the effect of the physician changing brand preferences due to an unsuitable product update interval must be addressed. When a manufacturer elects to update the PPI too frequently, the probability of the physician becoming disloyal due to product churn should increase. At the other end of the time scale, if the manufacturer does not update their product frequently enough, the probability of the physician becoming disloyal should also increase, due to the new product generations available from competing manufacturers. Therefore, we utilize a deterministic bathtub curve to represent the probability of a physician leaving the manufacturer for its competition as a function of the product update interval, $\theta$. An example of this effect is depicted in Figure 6. The manufacturer’s payoff function incorporates this by treating the proportion of physicians remaining with the manufacturer $1 - S(\theta)$ and the proportion of physicians adopting the new product generation prior to $\rho$ as independent quantities.

![Figure 6: Effect of Update Interval upon Probability of Switching](image)

Effects of Update Interval Upon Product Value

The third component of the manufacturer’s payoff function is to address the effect of the update interval upon the new product generation’s value. If the manufacturer releases product generations less frequently, it is likely that each generation will have greater value. Conversely, if new product generations are generated frequently, a PPI update will have less value. This is represented within the game by assuming a proportional relationship between the product update interval, $\theta$, and the product value, $V(\theta)$,
as a function of two input parameters, \( V(0) \) and \( V(\theta_{\text{max}}) \). This assumes that a drop in clinical value from one generation to another does not occur. The clinical value of the new product generation, \( V(\theta) \), scaled from zero to one as shown in Figure 7 is defined as

\[
V(\theta) = V(0) + \left( \frac{V(\theta_{\text{max}}) - V(0)}{\theta_{\text{max}}} \right) \theta.
\]

(8)

By incorporating these effects into the manufacturer’s payoff function, (1) can be restated as

\[
\begin{align*}
\int_{\omega_{\text{min}}-1}^{\rho} & \frac{1}{\beta(\lambda_1, \lambda_2(\rho, \omega, \lambda_1))} \left( \frac{x - \omega_{\text{min}} + 1}{\omega_{\text{max}} + 1 - \omega_{\text{min}} + 1} \right)^{\lambda_1-1} (1 - S(\theta)) \left[ V(0) + \left( \frac{V(\theta_{\text{max}}) - V(0)}{\theta_{\text{max}}} \right) \theta \right] d\tau
\end{align*}
\]

(9)

3.3.1.4 Physician’s Payoff

Like other players in standard supply chains, physicians may have economic motivations. However, unlike the typical producer-consumer relationship, physicians within the PPI supply chain do not pay for the supplies that they use. Without concern for cost, then, a physician’s objective is to maximize his clinical results. To capture this objective, we model the physician’s payoff to be the average clinical results during the PPI product generation’s lifecycle which can be represented by
While the manufacturer’s payoff decision is based upon diffusion theory, the physician’s payoff decision is based upon learning curve theory. The typical learning curve, defined in Konz and Johnson (2000), is of the form $Y = ax^b$, where $Y$ is the time to complete a given task, $a$ is the time to complete the first repetition of the task, $x$ is the number of repetitions, and $b$ is the shape of the learning curve. It is widely recognized that as workers repeat a task, the time to complete the task decreases as a function of the number of repetitions, asymptotically approaching a minimum time. Other authors recognize that the learning curve concept can describe how other performance metrics improve as the number of repetitions increases (Zangwill & Kantor 1998; Yelle 1979). In this way, we apply the concept of a learning curve to the physician’s clinical results payoff function.

As shown in Figure 8, a physician starts at an initial clinical results level, $R(0)$, while using the current PPI generation, until time $\omega$, when the new generation is adopted. After adoption, the clinical results suffer a drop due to the learning curve. This drop is tied to the degree of dissimilarity between successive generations. This is represented by $D(\omega)R(0)$, where the parameter $D(\omega)$ is the gap between the complexity of the new product generation and the physician’s knowledge of how to use that complexity successfully. This function can also be thought of as the risk the physician must accept when adopting a new PPI generation.
The maximum clinical results that the physician can achieve is tied directly to the clinical value \( V(\theta) \) of the new product generation: After performing \( L \) procedures with the new generation, the physician expects to achieve an improved level of clinical results of \( 1 + V(\theta) \) \( R(0) \), where \( V(\theta_{\text{max}}) \) indicates the maximum improvement in clinical results that can be achieved with the new generation’s technology. Based upon the demand for the procedure \( P \) and the manufacturer’s rollover decision \( \rho \), the physician may not perform the \( L \) procedures required to achieve maximum clinical results before the new product generation is phased out at \( \theta + \rho \).

To capture this process mathematically, the effects of adoption time upon peer learning, as well as the effects of player decisions upon the three piecewise segments of clinical results, must both be addressed.

**Effects of Adoption Time upon Peer Learning**

The average physician has some incentive to wait longer prior to adoption, because the longer he waits to adopt, the more he can learn from his peers prior to adoption. This reduces the potentially adverse impact of the new product generation upon his average clinical results. In this formulation, the peer learning acts as a counter-effect to the risk of adopting early, and it only improves upon the physician’s clinical results when they are below the initial level of clinical results, \( R(0) \). This concept is modeled by a linear relationship between \( D(\omega) \) and \( \omega \) such that

\[
D(\omega) = \begin{cases} 
D(0) + q\omega & , \quad \omega < \frac{1 - D(0)}{q} \\
1 & , \quad \omega \geq \frac{1 - D(0)}{q}
\end{cases}
\]

The parameter \( D(\omega) \) is then used to scale the initial clinical results, \( R(0) \) to represent the clinical results that would be experienced at the time of adoption (first use). \( D(\omega)R(0) \) is depicted as a dashed line in Figure 9.

To capture the three distinct phases of a physician’s clinical results as a function of the adoption decision, a piecewise function is necessary. Combining the effects of these time segments and the physician’s adoption decision upon peer learning into the learning curve concept leads to an expression for the physician’s clinical results,

\[
R(t) = \begin{cases} 
R(0) & , \quad if \quad t < t_1 \\
D(\omega)R(0) \left( t - \omega + \left( \frac{D(\omega)}{D(0)} \right)^{1/b} \right)^b & , \quad if \quad t_1 \leq t \leq t_2 \\
(1 + V(\theta)) \ast R(0) & , \quad t_2 < t < t_3,
\end{cases}
\]

where
The expressions for both the clinical results, \( R(t) \), and the learning curve shape parameter, \( b \), are derived directly from model input parameters. This derivation can be found in Appendix C.

\[
b = \frac{\ln \left( \frac{1 + V(\theta)}{D(\theta)} \right)}{\ln \left( \frac{1}{P} \right)}.
\]

**Effects of Player Decisions upon Piecewise Segments**

The first segment of the average physician’s clinical results function ends when either the manufacturer rollover policy occurs before the physician’s preferred adoption time (at \( t = \rho \)), or when the physician adopts the PPI update (at \( t = \omega \)). An indicator variable, \( x_1 \), is used to delineate which of these two scenarios occurs first for given values of \( \rho \) and \( \omega \). This variable is then used to define the cutoff for the first segment which is defined as

\[
t_1 = x_1 \rho + (1 - x_1) \omega,
\]

where

\[
x_1 = \begin{cases} 1 & , \rho < \omega \\ 0 & , \omega \leq \rho \end{cases}
\]
The second piecewise segment begins at $t_1$ and is cut off in a similar manner to the first segment, depending upon the players’ actions. This second cutoff occurs at one of three different points along the timeline. The first case occurs when the manufacturer’s rollover policy prevents the average physician from adopting at the preferred time ($\rho < \omega$), which leads to the truncation of the second segment at $t = \rho$. Otherwise, the physician proceeds through the learning curve until the end of the new product generation’s lifecycle ($\theta + \rho$), or the maximum clinical results are reached. (An expression for the time at which the maximum clinical results are reached is derived in Appendix C.) To represent this second cutoff, $t_2$, a second indicator variable, $x_2$, is introduced to define whether the maximum clinical results can be reached prior to the discontinuation of the new product generation. The second cutoff is given by

$$t_2 = (1 - x_1) \left[ x_2 (\theta + \rho) + (1 - x_2) \left( \left( \frac{1 + V(\theta)}{D(0)} \right)^{\frac{1}{b}} - \left( \frac{D(\omega)}{D(0)} \right)^{\frac{1}{b}} + \omega \right) \right] + x_1 \rho,$$

where

$$x_2 = \begin{cases} 
1 & , \theta + \rho < \left( \frac{1 + V(\theta)}{D(0)} \right)^{\frac{1}{b}} - \left( \frac{D(\omega)}{D(0)} \right)^{\frac{1}{b}} + \omega \\
0 & , \left( \frac{1 + V(\theta)}{D(0)} \right)^{\frac{1}{b}} - \left( \frac{D(\omega)}{D(0)} \right)^{\frac{1}{b}} + \omega \leq \theta + \rho
\end{cases} \tag{14}$$

Finally, the third piecewise segment, which begins at $t_2$, is truncated at $t_3$. This final segment ends when the new product generation’s lifecycle is completed ($t = \theta + \rho$) or the final segment is not reached because the manufacturer’s product rollover policy prevented the physician from implementing the preferred adoption time ($\rho < \omega$). If the latter case occurs, the values for all three segment cutoff points occur at the time the original product generation is discontinued ($t_1 = t_2 = t_3 = \rho$). The final end point is defined as

$$t_3 = x_1 \rho + (1 - x_1)(\theta + \rho). \tag{15}$$

Consolidating the segments into a single payoff function results in

$$u_{2,1} = \begin{cases} 
\frac{1}{t_3} \left[ \int_0^{t_1} R(0) dt + \int_{t_1}^{t_2} D(0) R(0) \left( t - \omega + \left( \frac{D(\omega)}{D(0)} \right)^{\frac{1}{b}} \right) dt + \int_{t_2}^{t_3} (1 + V(\theta)) R(0) dt \right] & , t_1 = 0 \\
\int_0^{t_1} R(0) dt + \int_{t_1}^{t_2} D(0) R(0) \left( t - \omega + \left( \frac{D(\omega)}{D(0)} \right)^{\frac{1}{b}} \right) dt + \int_{t_2}^{t_3} (1 + V(\theta)) R(0) dt & , \text{otherwise.}
\end{cases} \tag{16}$$

The details of the integration can be found in Appendix C.

### 3.3.2 Sales Rep Model and Notation
As in the original Manufacturer-Physician model, a two-player static game with complete information is used to address how the manufacturer’s sales rep impacts the optimal product update interval and adoption time decisions. In addition to the notation described in Tables 4 and 5, new notation is introduced and summarized here (Table 6) to incorporate the sales rep’s role into the game.

Table 6: Additional Notation for Sales Rep Model

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adoption time distribution for physician population</td>
<td>w</td>
<td>Right endpoint for adoption time distribution</td>
</tr>
<tr>
<td>Probability of physician switching to another manufacturer</td>
<td>S(θ_{max})</td>
<td>Percent of physician population switching manufacturers at maximum product update interval</td>
</tr>
<tr>
<td></td>
<td>p_S</td>
<td>Percent of maximum probability of switching reached after first month of development in concave scenario</td>
</tr>
<tr>
<td></td>
<td>f</td>
<td>Acceleration parameter for probability of switching curve in concave scenario</td>
</tr>
<tr>
<td>Clinical value of new product features</td>
<td>p_V</td>
<td>Percent of maximum product value gained after first month of development in concave scenario</td>
</tr>
<tr>
<td></td>
<td>g</td>
<td>Acceleration parameter for probability of switching curve in concave scenario</td>
</tr>
<tr>
<td>Physician’s clinical results</td>
<td>D'(0)</td>
<td>Drop in clinical results at time zero, adjusted for effects of sales rep</td>
</tr>
<tr>
<td></td>
<td>D' (ω)</td>
<td>Drop in clinical results as a function of ω, adjusted for effects of sales rep</td>
</tr>
<tr>
<td></td>
<td>L'</td>
<td>Number of cases to be completed to realize maximum value of product update, adjusted for effects of sales rep</td>
</tr>
<tr>
<td></td>
<td>b'</td>
<td>Shape parameter of learning curve, adjusted for effects of a sales rep</td>
</tr>
<tr>
<td></td>
<td>t_2'</td>
<td>Defines maximum domain of second segment of piecewise R(t) function, adjusted for effects of sales rep</td>
</tr>
<tr>
<td></td>
<td>a</td>
<td>Ability of sales rep, measured by percent reduction that the rep is able to reduce the risk of adopting (impact of D'(0)) and the number of procedures to master the product (L)</td>
</tr>
</tbody>
</table>

3.3.2.1 Players
The PPI manufacturer and physician remain as the only two players in the Sales Rep Model. Although the PPI sales rep is introduced in this new game, it is assumed that his incentives are aligned with the manufacturer in such a way that he is able to perfectly act in the manufacturer’s best interest.

3.3.2.2 Actions
The action space for the Sales Rep Model is equivalent to the action space utilized within the original Manufacturer-Physician formulation, as discussed in Section 3.3.1.2.

3.3.2.3 Manufacturer’s Payoff
In a sales approach using representatives, the manufacturer uses a sales rep to build relationships with the physician, as well as to provide product information and training. In order to further investigate the effects of these benefits upon the PPI supply chain, modifications to each player’s payoff function are required. As in the original model, the manufacturer’s payoff function is comprised of three main components: the proportion of physician population adopting the new product generation, the likelihood of losing physicians, and the anticipated product value. Minor changes are applied to each of these three components to account for the role the sales rep plays within the game. As stated previously, it is assumed that the sales rep acts on behalf of the manufacturer, and his incentives are perfectly aligned with the manufacturer’s success.

**Effects of the Sales Rep Upon Adoption Time**

In the Sales Rep Model, the probability distribution for the adoption time of the new PPI generation by the physician population is represented by the generalized beta distribution, which is consistent with the original Manufacturer-Physician model. However, previously, the adoption time distribution was influenced only by the manufacturer’s rollover policy. To account for reduction in variability of physician adoption times due to the influence of the sales rep, the beta distribution for adoption time is defined to be symmetric (i.e., $\lambda_2 = \lambda_1$), and the distribution parameters are decoupled from the rollover policy decision. In the original game, the right endpoint of the distribution was held constant at $\omega_{\text{max}} + 1$. In the Sales Rep Game, a new parameter ($w$) is introduced to represent this endpoint, which varies with the mean adoption time. The revised definition of the right endpoint maintains a symmetric curve when adoptions are not constrained by $\rho$. This is shown in Figure 10, where symmetric adoption time distributions are apparent. If the adoption time distribution would be constrained by $\rho$, then the endpoint is truncated to the end of the product’s availability on the market. Using (6) we can solve for the endpoint $w$, resulting in

$$w = \begin{cases} 2\omega & , 2\omega < \rho \\ \rho & , \rho \leq 2\omega. \end{cases}$$

This formulation reduces the variance surrounding the adoption time, accounting for the sales rep’s impact upon the adoption behavior of the physician population.
Effects of the Update Interval upon the Probability of Switching

The presence of the sales rep is purported to have a strong influence upon the loyalty of physicians (Robinson 2008; Montgomery and Schneller 2007; Schneller and Smeltzer 2006). This impact on loyalty is modeled in three different modes as shown in Figure 11.
In the first mode, the relationship between $S(\theta)$ and $\theta$ is constant at zero for all values of $\theta$. This is the extreme case of complete loyalty, where there is zero probability that physician’s will switching loyalties to a competing manufacturer. That is,

$$S(\theta) = 0, \quad \forall \theta$$ \hspace{1cm} (18)

This case can also be thought of as a scenario in which the sales rep is able to develop and maintain a very strong relationship with the physician in order to encourage brand loyalty. However, it is likely that even with an ideal sales rep, newer and more innovative PPI substitutions will become more prevalent in the marketplace as a given PPI generation gets older.

In this more likely scenario, $S(\theta)$ will accelerate as $\theta$ increases, despite the influence of the sales rep. In this case, $S(\theta)$ remains relatively low until a point, and then longer lifecycles result in increasing levels of disloyalty. In this case, the sales rep may have a positive influence early in the lifecycle, but becomes less impactful as $\theta$ increases. This scenario is the convex “Accelerated” curve shown in Figure 11. It has an exponential form, which is a function of the maximum value of the product update interval ($\theta_{\text{max}}$), the product update interval ($\theta$), and the maximum level that the probability of switching will reach ($S(\theta_{\text{max}})$) such that

$$S(\theta) = \frac{1}{(\theta_{\text{max}}/S(\theta_{\text{max}}))} \theta^2. \hspace{1cm} (19)$$

Finally, a third mode is defined to represent the likelihood of a physician switching to a competing manufacturer. In this last case, $S(\theta)$ ramps up quickly then trails off. This concave form represents a scenario in which an sales rep negatively impacts manufacturer-physician relationships shortly after a new PPI generation is introduced. This case, shown in Figure 11 as the “Immediate” curve, indicates a sales rep who performs poorly and drives physicians away. Representing this concave curve as a power function, we obtain

$$S(\theta) = p_S S(\theta_{\text{max}}) \theta^f$$ \hspace{1cm} (20)

where $f = \ln(1/p_S)/\ln(\theta_{\text{max}})$ and the parameter $p_S$ is introduced to represent the percent of the maximum switching probability that is reached after one month of the new R&D cycle. The slope of the curve, $f$, is found by substituting $S(\theta_{\text{max}})$ for $S(\theta)$, and $\theta_{\text{max}}$ for $\theta$.

**Effects of Update Interval Upon Product Value**

The final component of the manufacturer’s payoff function, product value, was identified as an important aspect of the PPI supply chain game in the Manufacturer-Physician game results. To investigate its
effect further, three modes are defined for the Sales Rep experiment to reflect several possible scenarios (Figure 12).

![Figure 12: Modified Effect of Update Interval upon Product Value](image)

A simple linear mode, consistent with the original product value in (8), is used. A second mode representing a scenario of diminishing returns over time has a concave shape and is defined as

$$V(\theta) = p_v V(\theta_{\text{max}}) \theta^a$$

(21)

where $g = \ln(1/p_v) / \ln(\theta_{\text{max}})$.

Finally, we define a convex option to capture the scenario in which a breakthrough in R&D is reached, and then the achievable value accelerates. This is defined as

$$V(\theta) = \frac{1}{(\theta_{\text{max}}^2 / p'(\theta_{\text{max}}))} \theta^2.$$  

(22)

Both the concave and convex forms for product value are formulated using an approach identical to the concave and convex functions defined for the probability of switching in the Sales Rep Model. Adding these modifications to the original manufacturer’s payoff function we obtain new payoff function

$$u_{1,II} =$$

$$\left[ \int_{\omega_{\text{min}}}^{\rho} \frac{1}{B(\lambda_1, \lambda_2)} \left( \frac{\tau - \omega_{\text{min}} + 1}{w - \omega_{\text{min}} + 1} \right)^{\lambda_1 - 1} \left( 1 - \frac{\tau - \omega_{\text{min}} + 1}{w - \omega_{\text{min}} + 1} \right)^{\lambda_2 - 1} d\tau \right] \left[ 1 - S(\theta) \right] V(\theta).$$

(23)
3.3.2.4 Physician’s Payoff

The physician’s payoff remains as the average clinical results over a product generation’s lifetime, with a similar form as (12) in Section 3.3.1.4 for the original Manufacturer-Physician game. However, several modifications are made here to account for the manufacturer’s use of sales representatives.

In the original Manufacturer-Physician model, the physician had to accept some risk of experiencing a reduction in his clinical results immediately following the adoption of a new product generation. If he waited for some time after the new product generation’s initial release, the initial drop in results at the time of adoption would improve due to peer learning that took place prior to adoption. In using sales representatives, the manufacturer is able to mitigate this risk for the physician by providing product information and training to the physician.

Although the sales rep’s effectiveness could potentially be considered a decision that the sales rep selects, we assume that the sales rep is properly incentivized to act in the manufacturer’s best interest. Aside from the sales rep’s personal payoffs, many conditions may impact the effectiveness of a sales rep in providing such information to his physicians. Some of these conditions include the number of physicians assigned to a sales rep, the sales rep’s innate abilities, and the infrastructure available for sales reps to share information with each other. While these, and other, possible factors are not addressed specifically, the parameter $a$ is introduced to indicate the sales rep’s general level of effectiveness.

The sales rep gain factor ($a$) is applied to two aspects of the physician’s learning. First, the sales rep gain factor is used to mitigate the physician’s risk at the time of adoption. This is accomplished by reducing the drop in clinical results when the product is initially released ($t = 0$) by a percentage. This modified drop in results is represented by $D'$ follows the same form as the original drop/peer learning function as is given by

$$
D'(\omega) = \begin{cases} 
D'(0) + q\omega, & \omega < \frac{1 - D'(0)}{q} \\
1, & \omega \geq \frac{1 - D'(0)}{q}
\end{cases}
$$

(24)

where $D'(0) = a + (1 - a)D(0)$.

In this formulation, the intercept represents the sales rep-mitigated risk, while the slope ($q$) continues to represent peer learning. The derivation of the expression for the adjusted drop at time zero, $D'(0)$, is available in Appendix C.
In addition to the above modification, the sales rep gain factor is used to reduce the time that the average physician requires to master the new PPI generation by a percent. This modified mastery time ($L'$) is defined as

$$L' = (1 - a)L.$$  \hfill (25)

The slope of the learning curve ($b$) is updated accordingly to $b'$, and the revised expression for the physician’s clinical results over time is

$$R(t) = \begin{cases} 
R(0), \text{if } t < t_1 \\
D'(0)R(0) \left( t - \omega + \left( \frac{D'(\omega)}{D'(0)} \right)^{1/b'} \right)^{b'}, \text{if } t_1 \leq t \leq t_2' \text{, where} \\
(1 + V(\theta))R(0), \text{if } t_2' < t < t_3, 
\end{cases}$$

$$b' = \frac{\ln\left(\frac{1 + V(\theta)}{D'(0)}\right)}{\ln\left(t_2'\right)}.$$  \hfill (26)

The effects of the player decisions upon the boundaries of the three piecewise segments of the clinical results function must reflect the sales rep scenario. While the first and third boundaries ($t_1$ and $t_3$) remain unaffected, the second boundary was modified to reflect the sales rep’s impact upon the length of the learning curve and the initial drop in results at the time of adoption. This results in

$$t_2' = (1 - x_1) \left[ x_2(\theta + \rho) + (1 - x_2) \left( \left( \frac{1 + V(\theta)}{D'(0)} \right)^{1/b} - \left( \frac{D'(\omega)}{D'(0)} \right)^{1/b} + \omega \right) \right] + x_1 \rho$$  \hfill (27)

where

$$x_2 = \begin{cases} 
1, \theta + \rho < \left( \frac{1 + V(\theta)}{D'(0)} \right)^{1/b} - \left( \frac{D'(\omega)}{D'(0)} \right)^{1/b} + \omega \\
0, \left( \frac{1 + V(\theta)}{D'(0)} \right)^{1/b} - \left( \frac{D'(\omega)}{D'(0)} \right)^{1/b} + \omega \leq \theta + \rho. 
\end{cases}$$

Incorporating these modifications into the physician’s payoff function we obtain

$$u_{2,11} = $$

$$= \begin{cases} 
\frac{1}{t_3} \left[ \int_0^{t_1} R(0)dt + \int_{t_2'}^{t_1} D'(0)R(0) \left( t - \omega + \left( \frac{D'(\omega)}{D'(0)} \right)^{1/b'} \right)^{b'} dt + \int_{t_2'}^{t_3} (1 + V(\theta))R(0)dt \right], \text{if } t_1 = 0 \\
\text{otherwise.} 
\end{cases}$$  \hfill (28)
3.3.3 Hospital Cost Control Model and Notation

To include the hospital in the PPI supply chain, the Sales Rep Model is extended to a three-player static game, with the hospital added as a third player. In this section the hospital’s payoff function and actions are presented. Following this, the subsequent modifications for the physician and manufacturer payoff functions are discussed. In addition to the general notation summarized in Table 4, additional notation specific to the Hospital Cost Control game is summarized in Table 7.

Table 7: Notation for Hospital Cost Control Model

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospital’s PPI Payoff</td>
<td>$k$</td>
<td>Claimed clinical value threshold (hospital’s decision)</td>
</tr>
<tr>
<td></td>
<td>$\alpha$</td>
<td>Importance of clinical innovation to hospital</td>
</tr>
<tr>
<td></td>
<td>$M$</td>
<td>Average claimed clinical value over time</td>
</tr>
<tr>
<td></td>
<td>$z$</td>
<td>Time index (Hospital’s perspective)</td>
</tr>
<tr>
<td></td>
<td>$C(z)$</td>
<td>Claimed clinical value over time</td>
</tr>
<tr>
<td></td>
<td>$\Delta$</td>
<td>Disparity between new generation’s actual value and claimed value</td>
</tr>
<tr>
<td></td>
<td>$\bar{V}(\theta, \Delta)$</td>
<td>Claimed clinical value of new product generation</td>
</tr>
<tr>
<td></td>
<td>$\bar{V}_{\text{min}}$</td>
<td>Minimum claimed clinical value of new product generation</td>
</tr>
<tr>
<td></td>
<td>$y$</td>
<td>Permission to adopt indicator variable, denoting if $k$ will restrict adoption</td>
</tr>
<tr>
<td></td>
<td>$z_1$</td>
<td>Defines maximum domain of first segment of piecewise $C(z)$ function</td>
</tr>
<tr>
<td></td>
<td>$z_2$</td>
<td>Defines maximum domain of second segment of piecewise $C(z)$ function</td>
</tr>
<tr>
<td></td>
<td>$H(V)$</td>
<td>Discrete random variable representing the probability of the physician switching to another hospital, as a function of the new generation’s actual value ($V(\theta)$)</td>
</tr>
</tbody>
</table>

3.3.3.1 Players

While the PPI manufacturer and the physician remain as players in the Hospital Cost Control model ($i = 1$ and 2, respectively), the hospital is added as the third player in this game ($i = 3$).
3.3.3.2 Actions

As in the first two models, the action space for the manufacturer, $A_1$, is comprised of feasible combinations of a product update interval decision ($\theta$), and a product rollover policy ($\rho$). Likewise, the physician’s action space, $A_2$, remains consistent with the previously games, containing a range of values for his adoption time decision ($\omega$). To incorporate the hospital as a player, a third action space is introduced. The hospital’s action space, $A_3$, consists of discrete values for the claimed product value threshold, or in other words, the maximum claimed value that the hospital is willing to pay for a single PPI unit. This decision is representative of the hospital price capping strategy highlighted in the literature, and is represented by $\kappa$. If the manufacturer’s claimed value (i.e., price) for the product exceeds the maximum value the hospital will accept, then the physician is unable to adopt the new PPI generation for use in procedures at the hospital. The initial (current state) price that the hospital pays for one unit of PPI is represented by the clinical value of the original product, $R(0)$.

3.3.3.3 Hospital’s Payoff

Given that hospitals are primarily motivated to have strong clinical results while controlling costs, the payoff function for the average hospital, $u_3$, is formulated as a tradeoff between the average clinical results that the physician achieves ($u_2$) and a proxy for the time average cost ($M$). Using $0 \leq \alpha \leq 1$ to represent this tradeoff, the payoff function for the hospital is given by

$$u_{3,\text{III}} = au_2 - (1 - \alpha)M.$$  \hspace{1cm} (29)

if the physician’s adoption is not constrained by the hospital. If the hospital imposes a constraint, then the payoff changes to

$$u_{3,\text{III}} = ((1 - H(V))[\alpha R(0) - (1 - \alpha)M]) - \{H(V)[au_2 - (1 - \alpha)M]\}$$ \hspace{1cm} (30)

where $H(V)$ is the probability that the physician will relocate his procedures to another facility. In this situation, the term $H(V)[\alpha u_2 - (1 - \alpha)M]$ is an opportunity cost for the hospital, representing the loss of $H(V)$ percent of the physician’s volume and its associated results and costs. If $z_2$ indicates the end of the new product generation’s lifecycle, then $M$ can be expressed as

$$M = \frac{1}{z_2} \int_0^{z_2} C(z)dz,$$ \hspace{1cm} (31)

where $C(z)$ represents the cost of the PPI to the hospital, over time. (As will be discussed later, there is a need to distinguish between the times that events occur from the physician’s perspective and the times that events occur from the hospital’s perspective. Because of this, the parameter $z$ is used to indicate the hospital’s timeline, whereas $t$ is used to represent time in the physician’s payoff function.) Because
the cost to the hospital is equivalent to the price charged by the manufacturer, the cost of the PPI is modeled here directly as product value.

Although the physician gradually progresses through a learning curve to achieve the maximum clinical value of a new PPI generation, the hospital must immediately pay for the maximum claimed value. Therefore, when a new PPI generation is adopted by the physician, the hospital’s cost will immediately step up from its initial level to the product’s claimed value as shown in Figure 13.

![Figure 13: Hospital Cost Function](image)

Prior to the physician’s adoption of the new PPI generation, the hospital’s cost is represented by the clinical value of the original product ($R(0)$). This cost remains constant until the physician elects to adopt the new PPI generation at $\omega$. Once the new PPI generation has been adopted, the cost to the hospital is driven by the value that the manufacturer claims for the new PPI ($\tilde{V}(\theta, \Delta)$). Unlike the two-player games, actual clinical value is distinguished here from claimed clinical value in order to account for any differences between the manufacturer’s perceptions and empirical results in the hospital.

**Effects of Value Disparity and Product Update Interval Upon Claimed Value**

The proxy used for the cost of the new PPI generation is "claimed clinical value", represented by $\tilde{V}(\theta, \Delta)$. The disparity between actual and claimed clinical value, $\Delta$, is modeled here as a characteristic of the
manufacturer. As shown in Figure 14, if this disparity is positive, then the manufacturer tends to over-value new PPI generations. Conversely, if the disparity is negative then the manufacturer typically under-values its new PPI generations. In line with the assumption that the new PPI generation will always be priced higher than the existing PPI generation, a minimum value for $\bar{V}(\theta, \Delta)$, referred to as $\bar{V}_{\text{min}}$ is defined.

![Figure 14: Claimed Value Function](image)

Using this definition of disparity between the claimed and actual clinical value, the claimed clinical value, $\bar{V}(\theta, \Delta)$, can be defined as

$$\bar{V}(\theta, \Delta) = \max(\bar{V}_{\text{min}}, V(\theta) + \Delta)$$

(32)

where $\bar{V}_{\text{min}} = 0.1V(\theta_{\text{max}})$. With this definition, the hospital’s cost can be expressed by a piecewise step function, given by

$$C(z) = \begin{cases} 
R(0) & \text{if } z < z_1 \\
R(0)[\bar{V}(\theta, \Delta) + 1] & \text{if } z_1 \leq z < z_2.
\end{cases}$$

(33)

In previous games, the maximum actual clinical results was expressed as $R(0)[V(\theta) + 1]$. It follows that the maximum clinical results claimed by the manufacturer can be represented by $R(0)[\bar{V}(\theta, \Delta) + 1]$. 
Effects of Player Decisions Upon Piecewise Segments

As with the physician’s learning curve, the breakpoints between the piecewise segments of the hospital’s cost function (33) are impacted by the timing of the players’ actions. The first segment of the hospital’s cost function starts at time zero ($z = 0$). Until the physician adopts the new generation, the hospital will continue to pay for the current generation, which is represented by the current clinical value, $R(0)$. As in earlier models, the point in time of the physician’s adoption is defined by the parameter $t_1$. However, if the hospital elects to constrain the physician’s adoption through price controls on the claimed value ($\tilde{V}(\theta, \Delta)$), then the physician may not be able to adopt the PPI.

If the actions selected by the hospital and the physician do not conflict, then the boundary between the two piecewise segments of $C(z)$ occurs at the boundary between the first two segments of the physician’s clinical results function (i.e., $z = z_1 = t_1 = t$). Likewise, the end of the horizon for both players occurs at $z = z_2 = t_3 = t$. However, if the hospital’s cap on claimed value prevents the physician from adopting the new PPI for use at that hospital, then the boundary between the two piecewise segments is equal to the end of the horizon ($z = z_1 = z_2 = t_3$), i.e., the hospital never pays for the new PPI. Although the hospital will not pay for the new generation, the physician could still adopt the new PPI generation for use at another hospital. In this case, the physician’s adoption still occurs at $t = t_1$, but the hospital’s cost function remains at the initial, lower level. In this case, $z = t_3 \neq t_1 = t$. In this case, $z \neq t$. Therefore, to clearly differentiate between the timing of events from the hospital’s perspective versus the physician’s perspective, we use $t$ to represent the timeline of the physician’s milestones (as in previous games), and we introduce $z$ for tracking the timing of events from the hospital’s perspective.

The first event, $z_1$, occurs when the new PPI generation is adopted in the hospital and is defined as

$$z_1 = (1 - y)t_1 + y t_3$$

(34)

where

$$y = \begin{cases} 
1 & , \kappa < \tilde{V}(\theta, \Delta) \\
0 & , \kappa \geq \tilde{V}(\theta, \Delta).
\end{cases}$$

A permission to adopt indicator variable, $y$, is introduced to indicate whether or not the hospital’s cap ($\kappa$) on claimed value ($\tilde{V}(\theta, \Delta)$) will permit the physician’s adoption. The second event, $z_2$, corresponds to the end of the new PPI generation’s lifecycle such that $z_2 = t_3$. Using these events, we can restate the hospital’s time average cost as

(35)
To simplify the notation moving forward, we refer to $M_{y=1}$ and $M_{y=0}$ when the value of $y$ must be stated explicitly. Otherwise, when $y$ may be either 0 or 1, the parameter $M$ is used. From the definitions given above, $M_{y=1}$ and $M_{y=0}$ are given by

$$
M = \begin{cases} 
\frac{1}{z_2} \left[ \int_0^{z_1} R(0) \, dz + \int_{z_1}^{z_2} R(0) [\bar{V}(\theta, \Delta) + 1] \, dz \right], & t_1 = 0 \\
\text{otherwise.} 
\end{cases}
$$

Effects of Claimed Value Cap Upon Player Payoffs

If the hospital's decision to cap claimed value prevents the physician from adopting the new PPI generation, then the physician will switch some portion of his PPI procedures, $H(\bar{V}(\theta))$, to another facility that permits the new PPI generation, and continue to perform the remainder of these procedures at the hospital $1 - H(\bar{V}(\theta))$. This translates to a fraction of the procedures being lost corresponding to $H(\bar{V}(\theta))$ for the hospital, and a fraction of unit sales lost corresponding to $1 - H(\bar{V}(\theta))$ for the manufacturer. Like $S(\theta)$, which represents the probability that the physician will switch his loyalties to a competing manufacturer, the function $H(\bar{V}(\theta))$ serves as an embedded decision. The permission to adopt indicator ($y$), and the physician’s adoption preference ($x_1$) are used together to determine if the hospital's action is disallowing the physician's adoption. (As discussed in Section 3.3.1.4, the parameter $x_1$ indicates whether the physician would benefit by adopting the new product generation before the manufacturer discontinues the original generation.) Given these two parameters, the expression $y(1 - x_1)$ indicates if a conflict exists between the physician’s adoption decision and the hospital’s claimed value cap. As shown in Table 8, four possible scenarios exist. The hospital and the physician only disagree in Scenario D, which occurs when the hospital restricts adoption and the physician wants to adopt the new generation.
If the players find themselves in Scenarios A, B, or C, then the payoff functions require no modifications as discussed up to this point. However, for Scenario D, the physician will perform the PPI procedures with a less restrictive hospital, with some probability $H(V(\theta))$.

Table 8: Hospital-Physician Agreement Scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Conditions</th>
<th>Hospital</th>
<th>Physician</th>
<th>$y(1-x_1)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>No restriction: $\kappa \geq \bar{V}(\theta,\Delta)$</td>
<td>$y = 0$</td>
<td>Does not want to adopt: $\rho &lt; \omega$</td>
<td>$x_1 = 1$</td>
</tr>
<tr>
<td>B</td>
<td>No restriction: $\kappa \geq \bar{V}(\theta,\Delta)$</td>
<td>$y = 0$</td>
<td>Does want to adopt: $\rho \geq \omega$</td>
<td>$x_1 = 0$</td>
</tr>
<tr>
<td>C</td>
<td>Restriction: $\kappa &lt; \bar{V}(\theta,\Delta)$</td>
<td>$y = 1$</td>
<td>Does not want to adopt: $\rho &lt; \omega$</td>
<td>$x_1 = 1$</td>
</tr>
<tr>
<td>D</td>
<td>Restriction: $\kappa &lt; \bar{V}(\theta,\Delta)$</td>
<td>$y = 1$</td>
<td>Does want to adopt: $\rho \geq \omega$</td>
<td>$x_1 = 0$</td>
</tr>
</tbody>
</table>

Effect of Product Value on Probability of Using Another Hospital

If the physician disagrees with hospital cost controls, he may elect to perform PPI procedures at a different hospital. Within the context of the three-player PPI game, the physician will only switch hospitals under Scenario D in Table 8. The physician’s payoff continues to be driven by the PPI’s actual clinical value. If the product’s actual clinical value is low, then the physician will be less likely to switch hospitals. However, if a new PPI generation has a high actual clinical value, it stands to reason that the physician will have a higher likelihood of switching to a hospital that will allow for the use of the new generation. To allow for switching behavior, we define the probability of using another hospital for PPI procedures, $H(V(\theta))$, as a simple linear function of $V(\theta)$ as shown in Figure 15 such that

$$H(V(\theta)) = \frac{H(V(\theta_{\text{max}}))}{V(\theta_{\text{max}})} V(\theta) .$$  

(38)
It is important to note that \( H(V(\theta)) \) is a function of the actual value of the new PPI generation, while the hospital’s costs over time is a function of the claimed value of the new PPI generation. Regardless of whether or not the hospital can differentiate between the claimed or actual clinical value, it will be pay for the claimed value (i.e., the cost of the product). As with the previous games, we assume that the physician can reasonably assess the actual clinical value of the new PPI generation, and is therefore motivated to adopt the new generation, and possibly switch hospitals, based upon this assessment.

If the physician decides to use another hospital for some portion of his procedures, then the hospital payoff is reduced to reflect this loss of patients. If the physician does not switch, then the benefits for procedures performed at the hospital will remain constant at \( R(0) \). As discussed above, this relationship only applies when both \( \kappa < \bar{\theta}(\theta, \Delta) \) and \( \rho \geq \omega \), or equivalently \( y(1 - x) = 1 \).

Given each of the effects described above, the hospital’s payoff function is given by

\[
u_{3,III} = \begin{cases} 
\frac{\alpha u_{2,II} - (1 - \alpha)M}{(1 - H(V))(\alpha R(0) - (1 - \alpha)M_{y=1}) - (H(V)(\alpha u_{2,II} - (1 - \alpha)M_{y=0}))}, & y(1 - x_1) = 0 \\
y(1 - x_1) = 1. & 
\end{cases} \tag{39}
\]

3.3.3.4 Physician’s Payoff

Although the hospital must pay for the new generation’s value, as claimed by the manufacturer, the clinical results achieved by the physician are still driven by the PPI’s actual clinical value. When the
game results in Scenarios A, B, or C, as defined in Table 8, the physician performs all PPI procedures at the hospital, and the physician payoff is not affected by the hospital’s cost controls. However, under the conditions of Scenario D, the physician will achieve clinical results based upon the new PPI generation for \( H(V(\theta)) \) of the procedures performed by diverting this portion of his procedures to another facility. For the remaining \( (1 - H(V(\theta))) \) of procedures, the physician will remain at the hospital, and the clinical outcomes for these procedures will result from the original PPI version. Modifying the physician’s payoff from the earlier games we obtain

\[
 u_{2,III} = \begin{cases} 
 u_{2,II} & , y(1 - x_1) = 0 \\
 (1 - H(V(\theta)))R(0) + H(V(\theta))u_{2,II} & , y(1 - x_1) = 1
\end{cases}
\]  

(40)

3.3.3.5 Manufacturer’s Payoff

Finally, with the introduction of the hospital as a player, the manufacturer’s payoff function must be adjusted in two ways. First, when the physician elects to adopt the new PPI generation, the proxy for price that the manufacturer receives from the hospital is the claimed product value, not the actual product value. Additionally, as with the other players, the manufacturer’s payoff may be impacted by the constraints that the hospital places upon physician adoption. When Scenarios A, B, or C occur, the manufacturer’s payoff is unchanged from earlier games. However, when the hospital’s payment policy conflicts with the physician’s adoption decision, the manufacturer’s payoff is also impacted. Under Scenario D, the physician’s adoption will not be limited for procedures performed at other facilities, or \( H(V) \) of the procedures performed. Therefore, in those cases, the manufacturer will receive the claimed product value of the new product. For other procedures performed within Scenario D, the hospital will only pay for the original PPI. This results in

\[
 u_{1,III} = \begin{cases} 
 \Pr(\tau \leq \rho)\left[ 1 - S(\theta) \right] \left[ \bar{V}(\theta, \Delta) \right] & , y(1 - x_1) = 0 \\
 H(V)\Pr(\tau \leq \rho)\left[ 1 - S(\theta) \right] \left[ \bar{V}(\theta, \Delta) \right] & , y(1 - x_1) = 1
\end{cases}
\]  

(41)

3.4 Experimental Approach

Due to the complexity of the players’ payoff functions, a closed form solution is not tractable. However, by defining a finite set of actions within each player’s action space, discrete payoffs can be represented using the normal form of the game.

In addition to assisting with the execution of model calculations, the decision to utilize a finite action space for each player is consistent with the actual scenarios. To illustrate this, consider the manufacturer’s
product update interval decision. It is possible for the manufacturer to select an action of releasing a new product generation at any point in time, but it is not probable that management would select an unusual interval. It is more reasonable for the manufacturer to release product generations consistent with standard business cycles, such as annually, biannually, or quarterly.

The manufacturer’s action space is defined to be the feasible combinations of values for both decisions, update interval ($\theta$) and rollover policy ($\rho$). We limit the manufacturer’s update interval decision to occur no more frequently than quarterly, and no less frequently than every six years, which leads to a set of twenty-four possible values for $\theta$. This lower bound is in line with the update interval cited by Joshi (2008), who indicated that the major manufacturers of cardiac devices may update products quarterly, or every three months. The manufacturer’s rollover policy is limited to a quarterly level as well, ranging from no overlap (“single product rollover”) to three years of overlap between the two product generations. This results in thirteen possible values for $\rho$. In accordance with the assumption that no more than two products generations are to be made available at the same time, all combinations in which $\rho$ is larger than $\theta$ are removed from the action space. This generates a manufacturer’s action space containing 272 possible actions. The average physician’s action space is defined to be the possible values for the physician’s adoption decision ($\omega$). We define the range of adoption values on a monthly basis, from 1 to 48 months following the release of the new product generation. Given these action spaces, a 13,056-cell bi-matrix can be used to represent both the Manufacturer-Physician Game and the Sales Rep Game. The three-player Hospital Cost Control Game utilizes a similar discrete-action space approach, with an additional action dimension that has six possible values for $\kappa$. This yields a tri-matrix cube with 78,336 possible combinations of decisions.

Ideally, the PPI supply chain games would utilize real world data to populate the model inputs. However, collecting data for the model parameters would entail observing product development and adoption activities over a time span of multiple years or perhaps decades. Therefore, this effort utilizes a full-factorial experiment in which a range of values is defined for each model input parameter, and a set of trials (games) are defined to represent the range of values for each parameter. This allows us to investigate the effects of different supply chain characteristics on the game.

Each set of model parameters was generated and the payoff functions were solved via Matlab. For each of the three scenarios, the pure Nash equilibria for the games were calculated. When multiple Nash equilibria occurred, the Pareto-ranking procedure described in Section 3.2.2 was applied. The Nash equilibria from all trials were then searched to identify any patterns and determine which model parameters tend to control the outcomes of the games. A description of this analysis is discussed in Section 4.1. Prior to that discussion, we define the full factorial experimental designs for each of the three PPI supply chain models in Sections 3.4.1, 3.4.2, and 3.4.3, respectively.
3.4.1 Full-Factorial Experiment Definition for Manufacturer-Physician Model

To investigate the Manufacturer-Physician product update game defined in Section 3.3.1.3, a full-factorial experiment is conducted on ten model input parameters, with at least two levels defined for each factor. The following discussion describes each factor, and the corresponding factor levels are summarized in Table 9. The remaining parameters were fixed to the values given in Table 10.

Table 9: Factor Levels for Manufacturer-Physician Game

<table>
<thead>
<tr>
<th>Factor</th>
<th>Factor Description</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability of Switching</td>
<td>$S(\theta)$ Defines the probability of switching as a function of the product update interval ($\theta$)</td>
<td>Options 1, 2, or 3 (as shown in Figure 16)</td>
</tr>
<tr>
<td>Adoption Time Distribution</td>
<td>$\rho_1$ Left endpoint of $\lambda_2$</td>
<td>9, 24 months</td>
</tr>
<tr>
<td></td>
<td>$\rho_{2A} = \rho_2 - \rho_1$ Defines right endpoint of $\lambda_2$ relative to left endpoint</td>
<td>9, 24 months</td>
</tr>
<tr>
<td></td>
<td>$k$ Maximum percent increase of $\lambda_2$</td>
<td>1.1, 4</td>
</tr>
<tr>
<td></td>
<td>$\lambda_1$ Given shape parameter for adoption time distribution</td>
<td>1.1, 4</td>
</tr>
<tr>
<td>Product Value</td>
<td>$V(\theta_{max})$ Clinical value of new product generation when $\theta = \max \theta$</td>
<td>0.1, 1</td>
</tr>
<tr>
<td>Physician Learning</td>
<td>$D(0)$ Percent drop of physician’s clinical results if adoption occurs when $t = 0$</td>
<td>10%, 75%</td>
</tr>
<tr>
<td></td>
<td>$q$ Constant relating $D$ and $\omega$, representing peer learning</td>
<td>0.005, 0.1</td>
</tr>
<tr>
<td></td>
<td>$L$ Number of procedures for physician to achieve maximum product value</td>
<td>15, 100 procedures</td>
</tr>
<tr>
<td></td>
<td>$P$ Number of patients physician sees each month</td>
<td>1, 10 patients</td>
</tr>
</tbody>
</table>

Table 10: Fixed Parameter Values for Manufacturer-Physician Game

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Parameter Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\max \omega$</td>
<td>Maximum value of adoption time in physician’s action space</td>
<td>48 months</td>
</tr>
<tr>
<td>$\min \omega$</td>
<td>Minimum value of adoption time in physician’s action space</td>
<td>1 month</td>
</tr>
<tr>
<td>$\max \theta$</td>
<td>Maximum value of product update interval in manufacturer’s action space</td>
<td>3 months</td>
</tr>
<tr>
<td>$\min \theta$</td>
<td>Minimum value of product update interval in manufacturer’s action space</td>
<td>72 months</td>
</tr>
<tr>
<td>$\max \rho$</td>
<td>Maximum value of rollover policy in manufacturer’s action space</td>
<td>3 months</td>
</tr>
<tr>
<td>$\min \rho$</td>
<td>Minimum value of rollover policy in manufacturer’s action space</td>
<td>48 months</td>
</tr>
<tr>
<td>$R(0)$</td>
<td>Physician’s clinical results at time zero</td>
<td>100</td>
</tr>
<tr>
<td>$V(0)$</td>
<td>Clinical value of new product generation when $\theta = 0$</td>
<td>0</td>
</tr>
</tbody>
</table>
Probability of Switching Factor

Preliminary experiments suggested that the Manufacturer-Physician game outcome could be particularly sensitive to the likelihood of a physician switching his preference to a competing product. Therefore the probability of switching as a function of the product update interval, $S(\theta)$, is included as an experimental factor. Three levels are utilized for this factor, as shown in Figure 16. First, a symmetric “bathtub” curve is used (as discussed in Section 3.3.1.3) in order to represent the tendency of a population of adopters that would be driven to competitors by a product update interval that is too rapid (too difficult to keep up with) or too slow (falling behind a competitor’s innovations). This is depicted as Option 1 in Figure 16. However, the probability of switching may not be symmetric across $\theta$, depending upon external factors such as the speed of innovation of the manufacturer’s competitors or the sensitivity of the physician population to frequent updates. To represent a physician population that is sensitive to frequent updates, but are purchasing a PPI that is not subject to much competitive innovation, we use Option 2 as shown in Figure 16. In this option, the probability of switching as a function of product update interval trails off as the product update interval increases. To represent a physician population that is less sensitive to frequent updates, but are purchasing a PPI that is a highly innovative market, we use Option 3 in Figure 16. In Option 3, the probability of switching undergoes a steep climb, and then levels off, as the product update interval increases.
Factors Impacting the Adoption Time Distribution

Four of the ten factors, $\rho_1, \rho_2, k$ and $\lambda_1$, are used within the manufacturer’s payoff function (7) to define the distribution of adoption times for the physician population. By definition, $\rho_2 > \rho_1$, so the factor $\rho_2$ is defined to ensure this relationship holds for every combination of trials within the full-factorial experiment. As described in Section 3.3.1.3, these parameters are used to change the shape of the manufacturer’s payoff function, and are used to reflect different types of physician population behavior.

Factors Impacting the Product Value

Another factor, $V(\theta_{max})$, governs how the value of the new product generation increases as the manufacturer’s product update interval, $\theta$, increases. As discussed in Section 3.3.1, the parameter $V(0)$ represents the percent of improvement from the new product generation over the initial clinical results, $R(0)$, when $\theta = 0$. The value of $V(0)$ is set to zero. This, combined with the factor, $V(\theta_{max})$, defines the value of $V$ for a given value of $\theta$ as given in (8).

Factors Impacting Physician Learning

The remaining four factors tested within the full-factorial experiment represent aspects of physician learning. The parameters $D(0)$ and $q$ are used to represent the drop in clinical results that the physician experiences when first adopting a PPI update. As detailed in Section 3.3.1.4, the drop decreases over time as the physician waits longer to adopt due to peer learning. The factors $L$ and $P$ represent how long it takes to master the update, and the volume of patients that the physician serves on a monthly basis.

In order to select reasonable values for these parameters, we refer to research from the medical field that investigates physician learning within specialties that commonly use PPIs. Several studies have investigated some aspects of the learning curve of orthopedic surgeons. For example, King et al. (2007) found that it took fifty iterations before physicians were able to “optimize” the positioning of the implant using a new minimally invasive arthroplasty procedure. This metric corresponds to factor $L$. Similarly, Nunley et al. (2009) studied the learning curve for hip resurfacing by orthopedic surgeons. Their results indicated that although it took less than 25 procedures for complications to be avoided by experienced physicians, it still took between 75 and 100 cases before the “desired component positioning” was achieved. Given that King et al. observed physicians performing fifty procedures prior to reaching the maximum clinical value ($L$), and Nunley et al. observed 75 to 100 procedures performed by physicians in order to reach ideal results, we use 100 as a maximum value for the factor $L$. In order to observe the impact of fast learning, we use 15 procedures as an extreme minimum value for $L$.

King et al. (2007) also found that it took 25 procedures for orthopedic surgeons performing minimally invasive arthroplasty to achieve the same operative time that they achieved using the traditional method.
The operative time for the new procedure (102.5 minutes) took 30% longer than the traditional procedure (78.9 minutes), when looking at the first quartile of the new procedures. We use this 30% as a benchmark for $D(0)$ which we test at 10% and 75% in order to represent extreme values.

Similar empirical studies have been performed to investigate the effects of patient volume on physicians’ clinical results, which corresponds to factor $P$. Munoz et al. (1990) categorized orthopedic surgeons an academic medical center as “low volume” surgeons if they performed less than five procedures of a specific nature in three years, and as “high volume” surgeons if they performed eight or more of the procedures in the same time frame. More recently, when studying orthopedic surgeons performing knee arthroplasty, Katz et al. (2007) classified physicians that completed less than six procedures a year to be “low volume”. In line with the classification by Katz et al., a low factor level of 6 procedures a year, or less than 1 patient each month, may be appropriate for the model input $P$. Unlike the bounds described by Munoz et al. and Katz et al., Nunley et al. (2009) depicts high volume physicians as those who performed 100 to 150 procedures within sixteen months. In order to account for this wide range in physician volume, which also may vary across specialties, we use a factor level of 1 procedure per month (12 per year) to represent the low-volume physician, and a level of 10 procedures per month (120 per year) for the high-volume physician.

The full-factorial experiment consists of a set of 1,536 trials, one for each possible combination of the factor levels. For each trial, which corresponds to a normal form game, the pure Nash equilibria were calculated, and when necessary, the resulting equilibria were Pareto-ranked. Results from this experiment are presented in Section 4.2.

3.4.2 Full-Factorial Experiment Definition for Sales Rep Model

To investigate the effects of the Sales Rep Game defined in Section 3.3.2, a full-factorial experiment is conducted on model input parameters, with at least two levels defined for each factor. The following discussion describes each factor, and the corresponding factor levels are summarized in Table 11. The remaining parameters were fixed to the values given in Table 12.

Factors Impacting Adoption Time Distribution

As with the Manufacturer-Physician full-factorial experiment, the beta distribution shape parameter ($\lambda_1$) is set to both a high and low factor level. The shape parameter values used for the Sales Rep Model experiment are equivalent to the values used in the previous experiment.
Probability of Switching Factor

As previously discussed, it is important to consider several scenarios for the probability of switching factor, due to the widespread belief within the healthcare industry that the sales rep plays an important role in influencing the loyalty of physicians. To that end, several forms were presented in Section 3.3.2.3. The first form, representing 100% physician loyalty, requires no additional input parameters. However, the remaining two forms are a function of the maximum probability of switching ($S(\theta_{max})$), when the product update interval is at its highest value in the action space ($\max \theta = 72$ months). In order to provide a range of shapes, and to gain insights on the worst-case effects of this parameter, two levels of the maximum probability of switching are considered.

Table 11: Factor Levels for Sales Rep Game

<table>
<thead>
<tr>
<th>Factor</th>
<th>Factor Description</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability of Switching</td>
<td>$S(\theta)$ Defines the probability of switching as a function of the product update interval ($\theta$)</td>
<td>100% Loyalty, Immediate, or Accelerated (as shown in Figure 11)</td>
</tr>
<tr>
<td></td>
<td>$S(\theta_{max})$ Probability of switching manufacturers when $\theta = \max \theta$</td>
<td>10%, 100%</td>
</tr>
<tr>
<td>Adoption Time Probability Distribution</td>
<td>$\lambda_1$ Shape parameter for adoption time probability distribution function</td>
<td>1.1, 4</td>
</tr>
<tr>
<td>Product Value</td>
<td>$V(\theta)$ Clinical value of new product generation as a function of the product update interval ($\theta$)</td>
<td>Original (Linear), Diminishing Returns, or Threshold Achieved (as shown in Figure 12)</td>
</tr>
<tr>
<td></td>
<td>$V(\theta_{max})$ Clinical value of new product generation when $\theta = \max \theta$</td>
<td>10%, 100%</td>
</tr>
<tr>
<td>Physician Learning</td>
<td>$L$ Number of procedures for physician to achieve maximum product value</td>
<td>15, 75 procedures</td>
</tr>
<tr>
<td></td>
<td>$q$ Constant relating $D$ and $\omega$, representing peer learning</td>
<td>0.005, 0.1</td>
</tr>
<tr>
<td></td>
<td>$a$ Sales rep gain factor; Reduction of $L$ produced by sales rep-provided training</td>
<td>10%, 80%</td>
</tr>
<tr>
<td></td>
<td>$D(0)$ Percent drop of physician’s clinical results if adoption occurs when $t = 0$</td>
<td>10%, 75%</td>
</tr>
<tr>
<td></td>
<td>$P$ Number of patients physician sees each month</td>
<td>1, 10 patients</td>
</tr>
</tbody>
</table>
Table 12: Fixed Values for Sales Rep Game

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Parameter Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\max \omega$</td>
<td>Maximum value of adoption time in physician’s action space</td>
<td>48 months</td>
</tr>
<tr>
<td>$\min \omega$</td>
<td>Minimum value of adoption time in physician’s action space</td>
<td>1 month</td>
</tr>
<tr>
<td>$\max \theta$</td>
<td>Maximum value of product update interval in manufacturer’s action space</td>
<td>72 months</td>
</tr>
<tr>
<td>$\min \theta$</td>
<td>Minimum value of product update interval in manufacturer’s action space</td>
<td>3 months</td>
</tr>
<tr>
<td>$\max \rho$</td>
<td>Maximum value of rollover policy in manufacturer’s action space</td>
<td>48 months</td>
</tr>
<tr>
<td>$\min \rho$</td>
<td>Minimum value of rollover policy in manufacturer’s action space</td>
<td>3 months</td>
</tr>
<tr>
<td>$R(0)$</td>
<td>Physician’s clinical results at time zero</td>
<td>100</td>
</tr>
<tr>
<td>$V(0)$</td>
<td>Clinical value of new product generation when $\theta = 0$</td>
<td>0.4</td>
</tr>
<tr>
<td>$p_V$</td>
<td>Value of product after 1 month of product development cycle</td>
<td>0.4</td>
</tr>
<tr>
<td>$p_s$</td>
<td>Probability of switching after 1 month of product development cycle</td>
<td>0.4</td>
</tr>
</tbody>
</table>

Factors Impacting the Product Value

As discussed in Section 3.2.4, the product value is defined to be one of three forms: Original (linear), Diminishing Returns (concave), or Threshold (convex). Each of these three forms represents possible relationships between the manufacturer’s product update interval ($\theta$) and the new product generation’s value ($V(\theta)$). Although each of these relationships approach the maximum product value ($V(\theta_{max})$) via a different path, they each intercept the origin. To test the impact of the maximum product value, each of the three forms are tested at a low maximum value (a 10% improvement over $R(0)$) and at a high maximum value (a 100% improvement over $R(0)$). These factor levels for the maximum product value are in line with values used in the original Manufacturer-Physician experiment.

Factors Impacting Physician Learning

As discussed in Section 3.4.1, the factors $L$ and $P$ represent how long it takes to master the update, and the volume of patients that the physician serves on a monthly basis, respectively. Values for these parameters in the Sales Rep Model are similar to values used in the Manufacturer-Physician model. The highest level tested for $L$ here is 75 procedures to achieve maximum value. Levels used for the peer learning parameter ($q$) are equivalent to those used in the original model. Additionally, a high (25%) and low (5%) level are included for the sales rep gain factor ($a$), which represents the sales rep’s training effectiveness.

Trials with factor level combinations that resulted in a condition of $0 < \frac{L'}{P} < 1$ were removed from consideration, because this particular condition results in a learning curve with an inverted shape. Following the enumeration of all possible trials, and the removal of those meeting this condition, the experimental results for the Sales Rep Game are based upon 1,680 trials.
### 3.2.6.3 Full-Factorial Experiment Definition for Hospital Cost Control Model

Following the definition of the Hospital Cost Control model presented in Section 3.3.3, model input parameters are defined as factors in a full-factorial experiment to allow for the study of behaviors that may occur within the three player PPI supply chain. The levels defined for each of the factors studied here are summarized in Table 13, and the remaining parameters are set to fixed input values as shown in Table 14. As in the Sales Rep Game, factor level combinations which result in \( 0 < \frac{L'}{T} < 1 \) were eliminated from the experiment. This resulted in 3,240 trials. Each factor tested in this experiment is discussed below.

**Table 13: Factor Levels for Hospital Cost Control Game**

<table>
<thead>
<tr>
<th>Factor</th>
<th>Factor Description</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability of Switching</td>
<td>( S(\theta) ) Defines the probability of switching as a function of the product update interval ( (\theta) )</td>
<td>100% Loyalty, Immediate, or Accelerated (as shown in Figure 11)</td>
</tr>
<tr>
<td></td>
<td>( S(\theta_{\text{max}}) ) Probability of switching manufacturers when ( \theta = \max \theta )</td>
<td>10%, 100%</td>
</tr>
<tr>
<td>Adoption Time Probability Distribution</td>
<td>( \lambda_1 ) Shape parameter for adoption time probability distribution function</td>
<td>1.1, 4</td>
</tr>
<tr>
<td>Product Value</td>
<td>( V(\theta) ) Clinical value of new product generation as a function of the product update interval ( (\theta) )</td>
<td>Original (Linear), Diminishing Returns, or Threshold Achieved (as shown in Figure 12)</td>
</tr>
<tr>
<td></td>
<td>( V(\theta_{\text{max}}) ) Clinical value of new product generation when ( \theta = \max \theta )</td>
<td>10%, 100%</td>
</tr>
<tr>
<td>Physician Learning</td>
<td>( L ) Number of procedures for physician to achieve maximum product value</td>
<td>15, 75 procedures</td>
</tr>
<tr>
<td></td>
<td>( q ) Constant relating ( D ) and ( \omega ), representing peer learning</td>
<td>0.005, 0.1</td>
</tr>
<tr>
<td></td>
<td>( a ) Sales rep gain factor; Reduction of ( L ) produced by sales rep-provided training</td>
<td>80%</td>
</tr>
<tr>
<td></td>
<td>( D(0) ) Percent drop of physician’s clinical results if adoption occurs when ( t = 0 )</td>
<td>10%</td>
</tr>
<tr>
<td></td>
<td>( p ) Number of patients physician sees each month</td>
<td>1, 10 patients</td>
</tr>
<tr>
<td>Weight of Clinical Results</td>
<td>( \alpha ) Importance of clinical results to hospital</td>
<td>25%, 50%, 75%</td>
</tr>
<tr>
<td>Claimed Value</td>
<td>( \bar{V}_{\text{min}} ) Minimum claimed value of new product generation when ( \theta = \max \theta )</td>
<td>10%</td>
</tr>
<tr>
<td></td>
<td>( \Delta ) Disparity between new generation’s actual value and claimed value</td>
<td>-25%, 0%, 25%</td>
</tr>
<tr>
<td>Probability of Switching Procedure Location</td>
<td>( H(V(\theta_{\text{max}})) ) Probability of the physician switching to another hospital when ( V(\theta) = V(\theta_{\text{max}}) )</td>
<td>10%, 100%</td>
</tr>
</tbody>
</table>
Table 14: Fixed Values for Hospital Cost Control Game

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Parameter Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>max $\omega$</td>
<td>Maximum value of adoption time in physician’s action space</td>
<td>48 months</td>
</tr>
<tr>
<td>min $\omega$</td>
<td>Minimum value of adoption time in physician’s action space</td>
<td>1 month</td>
</tr>
<tr>
<td>max $\theta$</td>
<td>Maximum value of product update interval in manufacturer’s action space</td>
<td>72 months</td>
</tr>
<tr>
<td>min $\theta$</td>
<td>Minimum value of product update interval in manufacturer’s action space</td>
<td>3 months</td>
</tr>
<tr>
<td>max $\rho$</td>
<td>Maximum value of rollover policy in manufacturer’s action space</td>
<td>48 months</td>
</tr>
<tr>
<td>min $\rho$</td>
<td>Minimum value of rollover policy in manufacturer’s action space</td>
<td>3 months</td>
</tr>
<tr>
<td>$R(0)$</td>
<td>Physician’s clinical results at time zero</td>
<td>100</td>
</tr>
<tr>
<td>$V(0)$</td>
<td>Clinical value of new product generation when $\theta = 0$</td>
<td>0</td>
</tr>
<tr>
<td>$p_V$</td>
<td>Value of product after 1 month of product development cycle</td>
<td>0.4</td>
</tr>
<tr>
<td>$p_S$</td>
<td>Probability of switching after 1 month of product development cycle</td>
<td>0.4</td>
</tr>
</tbody>
</table>

Factors Impacting Adoption Time Distribution

Experiments for the first two games set the beta distribution shape parameter ($\lambda_1$) to both a high and low factor level. In these experiments, this factor was not found to be a distinguishing characteristic, therefore it is only set to the high factor level.

Probability of Switching Factor

The factors which impact the probability of switching are defined in a manner equivalent to the Sales Rep game. This includes the three possible forms presented in Section 3.3.2.3, as well as both a high and low factor level for the maximum probability of switching ($S(\theta_{\text{max}})$).

Factors Impacting the Product Value

Similarly, the factors impacting the actual product value are unchanged from the Sales Rep game. As discussed in Section 3.3.2, the product value is defined to be one of three forms: Original (linear), Diminishing Returns (concave), or Threshold (convex). The original high and low factor levels for the maximum product value ($V(\theta_{\text{max}}) = 100\%$ and $10\%$, respectively), is applied to each of the three forms.

Factors Impacting Claimed Value

Unlike earlier games, the Hospital Cost Control game introduces the concept of “claimed value” versus “actual value” of the new product generation, as defined in Section 3.3.2.3. In order to test a range of the manufacturer’s valuation tendency, the parameter $\Delta$, which is used to offset the claimed value from the actual value, is tested at three levels (-25%, 0%, and 25%). Both positive and negative values are included here in order to simulate the effects over-valuing and under-valuing the new product generation. Additionally, the parameter $\bar{\nu}_{\text{min}}$ is used to ensure that the claimed value does not conflict with the
assumption that the manufacturer believes the new product generation to be more valuable than earlier
generations. A single factor level (10%) is used as input for this parameter.

Factors Impacting Physician Learning
While some factor levels for parameters impacting physician learning ($L$ and $P$) remain unchanged from
the Sales Rep Game, others are held to a single value. The factor representing the initial clinical drop
due to physician adoption ($D(0)$) is set to the low value (10%). Likewise, the peer learning factor ($q$) is
set to the low level used in earlier experiments (0.005). Finally, the sales rep gain factor ($a$) is set to be
an effective sales rep, at 80%. These levels for these factors are discussed in more detail in Sections
3.4.1 and 3.4.2, respectively.

Probability of Changing Hospitals Factor
While some trade publications indicate it is likely for physicians to divert patients to competing hospitals,
no literature which closely studied this assumption was found. Therefore, we test the factor $H(V(\theta_{max}))$
at extreme high (100%) and low (10%) values.
4. Experimental Results

Following the definition of the full-factorial experiments, results were analyzed for trends and systemic behavior. Section 4.1 describes a common structure for this analysis, which is repeated in Sections 4.2 through 4.4 for each of the three PPI supply chain games.

4.1 Analysis of Results

A common analysis approach was applied to the full-factorial experimental results for each of the three PPI supply chain games. First, the general form of the payoff functions across the players’ action space is discussed. Payoffs are normalized and classified into similar outcomes. Then, a supervised learning algorithm is applied to understand what player characteristics distinguish between the payoff classes. Finally, the equilibria actions are mapped to the payoff classes in order to gain insights into the effects of player decisions upon expected payoffs. Each of these analysis steps is described in detail below.

Understanding the General Form of Payoffs

In order to observe the general behavior of the payoff functions, a single trial from the full-factorial experiment was selected. A contour plot of the players’ payoffs across the action space shows how the surface of the payoffs varies based upon the players’ decisions. Additionally, each player’s payoff function was plotted over each of the player’s decisions, while other decisions were held constant. These plots indicate the general behavior of the payoff functions across the action space.

Identifying Distinguishing Characteristics

A supervised learning approach (classification) was used to analyze the full factorial experiment results in order to understand which characteristics of a physician and manufacturer distinguish between different classes of payoff outcomes. To achieve this end, the full-factorial experiment results were refined in three steps. First, we considered only the top-ranked Nash equilibria payoff(s) for each trial which were determined with the Pareto-ranking procedure described in Section 3.2.2. Then, the expected payoff outcomes were normalized across trials. Finally, the trials were grouped into payoff classes by observing the frequency that each combination of normalized payoff pairs \((u_1, u_2)\) or tuples \((u_1, u_2, u_3)\) occurred. The supervised learning approach classified the data into payoff classes (the predicted attribute) using the model input parameters as descriptive attributes to differentiate between trials. The results of the classification were used to identify which of the descriptive attributes play a role in distinguishing between the payoff classes.

A standard decision tree algorithm, C4.5, was used to perform the classification. The C4.5 algorithm generates a tree from a top-down approach, which starts with the entire training dataset and breaks it into smaller subsets as it moves down the tree (Han and Kamber 2006). Other algorithms, such as ID3 and
CART also use this top-down approach. However, the C4.5 algorithm allows multiple splits to occur from a single node, while CART allows for only binary splits (Han and Kamber 2006). Additionally, while both ID3 and C4.5 use the concept of information gain to select an attribute to partition the data at a given node, C4.5 provides a refinement to the ID3 approach. C4.5 uses a "normalized" approach to information gain in order to remove some bias toward attributes with many values that is present within ID3 (Han and Kamber 2006). We used the C4.5 algorithm in the open-sourced data mining tool, Weka (Hall et al. 2009).

When applying a supervised learning approach, data are separated into a training set, which the classification algorithm uses to create a decision tree (the "learning step"), and a test set, to which the tree is applied to test for accuracy. The k-fold cross-validation test approach expands this concept. In k-fold cross-validation, the original data set is divided into k subsets, or folds. The learning step is performed using k-1 folds and then tested upon the remaining fold that was omitted from the learning step. This is repeated k times, leaving out a different fold for each iteration of the learning step. Then the results of each fold are combined to estimate the tree’s overall accuracy (Han and Kamber 2006). We used a 10-fold cross validation approach to determine the accuracy of our decision tree classification results.

Based upon the classification results, further analysis was performed around the specific input parameters as warranted. In these cases, an additional full-factorial experiment was performed, in which additional levels are introduced for the key model input parameters, and the other input parameters were held constant. This general approach for the analysis of the game results was applied to each of the three PPI supply chain games in Sections 4.2, 4.3, and 4.4.

4.2 Manufacturer-Physician Game Results

Using the numerical values defined in Section 3.2.6.1, the values for the payoff functions, \( u_1 \) and \( u_2 \), were calculated for each combination of player strategies in the action space in order to generate a normal form representation for each trial. In line with the approach described in Section 4.1, the following results are discussed below: 1) General form of payoffs 2) Classification of payoffs, 3) Detailed analysis of selected attributes, and 4) Relationships observed between predicted actions and payoffs.

4.2.1 General Behavior of Game

The full-factorial experiment defined over 1,500 normal form games generated 13,506 values for both \( u_1 \) and \( u_2 \) per game. The interaction of the payoff surfaces are described through the calculation of pure Nash equilibria, as described in Section 3.2.2. Although the shape of these surfaces varies based upon the model input parameters, it is possible to observe some effects from the input parameters upon the form of the payoff functions of a single trial. Figures 17 and 18 depict the manufacturer and physician
payoff functions, respectively, calculated from a single trial. A summary of the input parameter values for the selected trial are given in Table 15. The Nash equilibrium for this trial occurs at $\theta = 72$ months, $\rho = 48$ months, and $\omega = 9$ months and is indicated by red arrows in Figures 17 and 18.

Table 15: Factor Levels for Example Payoffs

<table>
<thead>
<tr>
<th>Factor</th>
<th>Factor Description</th>
<th>Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability of Switching</td>
<td>$S(\theta)$ Defines the probability of switching as a function of the product update interval ($\theta$)</td>
<td>Option 2 (Sensitive to frequent updates)</td>
</tr>
<tr>
<td>$\rho_1$</td>
<td>Left endpoint of $\lambda_2$</td>
<td>9 months</td>
</tr>
<tr>
<td>$\rho_{2A} = \rho_2 - \rho_1$</td>
<td>Defines right endpoint of $\lambda_2$ relative to left endpoint</td>
<td>9 months</td>
</tr>
<tr>
<td>$k$</td>
<td>Maximum percent increase of $\lambda_2$</td>
<td>1.1</td>
</tr>
<tr>
<td>$\lambda_1$</td>
<td>Given shape parameter for adoption time distribution</td>
<td>1.1</td>
</tr>
<tr>
<td>Product Value</td>
<td>$V(\theta_{\text{max}})$ Clinical value of new product generation when $\theta = \max \theta$</td>
<td>1</td>
</tr>
<tr>
<td>Physician Learning</td>
<td>$D(0)$ Percent drop of physician’s clinical results if adoption occurs when $t = 0$</td>
<td>0.1</td>
</tr>
<tr>
<td>$q$</td>
<td>Constant relating $D$ and $\omega$, representing peer learning</td>
<td>0.1</td>
</tr>
<tr>
<td>$L$</td>
<td>Number of procedures for physician to achieve maximum product value</td>
<td>100 procedures</td>
</tr>
<tr>
<td>$P$</td>
<td>Number of patients physician sees each month</td>
<td>1 patient</td>
</tr>
</tbody>
</table>

Figure 17: Manufacturer’s Payoff Function
In Figure 17, the manufacturer’s payoff, $u_1$, can be seen for every combination of players’ actions for the selected trial. The effects of the adoption time probability distribution can be seen in the $A_2$ dimension: as the physician selects a smaller value of $\omega$, the proportion of physicians adopting before $\rho$ increases. Along the dimension of the manufacturer’s actions, $A_1$, numerous peaks are present. (The manufacturer’s action space, $A_1$, is comprised of all feasible combinations of $\rho$ and $\theta$.) Each of the groupings in this dimension corresponds to $\rho$, within which, each value of the manufacturer’s payoff is associated with a value of $\theta$. This illustrates that, for this particular trial, the manufacturer benefits from small $\omega$ values; however, the manufacturer’s benefit from a small $\omega$ is very sensitive to $\theta$. When considering that higher values of $A_1$ correspond to higher values of $\rho$, it is possible to observe how the manufacturer’s payoff becomes less sensitive to $\omega$ as $\rho$ increases. This is not unexpected, as the effect of $\rho$ on the shape parameter, $A_2$, (7) acts to increase the variance of $\omega$ as $\rho$ increases.

The average physician’s payoff, $u_2$, as shown in Figure 18 illustrates the impact of the physician’s learning curve. As $\omega$ increases past the optimal adoption time, the physician’s expected results decrease. This is because it is not possible to gain the maximum benefits of the new product generation during its lifecycle with a later adoption. As $\omega$ continues to increase, the physician’s payoff tapers into a flat region.
covering a large portion of the action space where the payoff function reaches a minimum. This region indicates the action combinations for which the physician prefers to reject the new product generation and remain at his current level of clinical results. In the \( A_1 \) dimension, the peaks, which follow a repetitive pattern similar to the manufacturer’s payoff function, are truncated by \( \rho \). The highest point of each range occurs at an \( \omega \) for which the physician is able to balance effort of learning with knowledge gained from peers.

Figure 19: Manufacturer’s Payoff Across \( \theta \) (Constant \( \omega \))

Figure 20: Manufacturer’s Payoff Across \( \theta \) (Constant \( \rho \))
Figure 21: Manufacturer’s Payoff Across $\rho$ (Constant $\omega$)

Figure 22: Manufacturer’s Payoff Across $\rho$ (Constant $\theta$)
Figure 23: Physician's Payoff Across $\omega$ (Constant $\rho$)

Figure 24: Physician's Payoff Across $\omega$ (Constant $\theta$)
Additional views of the payoff functions for the selected trial are given in Figures 19-24. These figures chart each player payoff as a function of the player decisions ($\theta, \rho$, and $\omega$). In the case of the manufacturer, a separate figure is provided for $\theta$ and $\rho$, in order to more clearly depict the effects of each decision upon the payoff function. In each plot, one decision is held constant, and one decision is shown on the independent x-axis. The effects of the remaining decision are shown via a separate series on each chart. Each series corresponds to a given constant value for the third decision variable.

As with Figures 17 and 18, we see from the charts in Figures 19-24 that the general forms of the payoff functions are well-behaved. Figures 19 and 20 demonstrate that $u_1$ increases proportionally with respect to $\theta$, when $\rho$ provides an incentive for the physician to adopt. In the second set of charts (Figures 21 and 22), we also see a positive correlation between high values of $\rho$ and high values for $u_1$. However, this correlation is clearly constrained by the two decisions ($\theta, \omega$). For example, while $u_1$ increases as $\rho$ increases, we also see that this effect is much greater for a higher value of $\theta$. Similarly, $\omega$ plays a dramatic role in the magnitude of the impact that $\rho$ will have upon $u_1$. Specifically, in Figure 19, we see that for lower values of $\theta$, $u_1$ reaches a threshold at $\rho = \theta$, at which $u_1$ does not exist. This is because decisions where $\theta \leq \rho$ are omitted from the action space. Higher values of $\theta$ are not affected by the $\rho = \theta$ threshold because the manufacturer’s action space is limited to values of $\rho < 48$. In Figure 22 we see a similar threshold at $\rho = \theta$. Figure 22 also shows the impact of the average physician adopting sooner. When the average physician adopts earlier, his lagging peers are more likely to adopt the product update before it is discontinued. As more of the population is inclined to adopt later ($\omega$ increases), the shape of the payoff function in this dimension changes. This change reflects the nonlinear relationship between $\omega$ and $u_1$. For example, when the average physician adopts early ($\omega = 1$), there are few values of $\rho$ that truncate the cumulative probability function, and a large proportion of the physician population will adopt. As $\omega$ increases, more values of $\rho$ within the action space affect the calculation of this function. In other words, more physicians’ natural adoption time will become infeasible due to the manufacturer’s selection of $\rho$.

Finally, in Figures 23 and 24, we see that $u_2$ is clearly impacted by his adoption time decision. Figures 23 and 24 exhibit similar forms: As $\omega$ increases, $u_2$ increases until he has gained all benefits possible from peer learning, in this case when $\omega = 9$ months. In these figures we can observe the tradeoff between peer learning and adopting soon enough to reap benefits of a product update before it is discontinued. As long as the manufacturer selects actions that would encourage the physician’s adoption, we see the same adoption time to be optimal for the physician. These figures also depict the effects of $\omega > \rho$ upon $u_2$. Because adoption after product discontinuation is not feasible, these scenarios indicate that the physician would not adopt the new product generation. In these cases, we see a constant value for $u_2$. 
equivalent to \( R(0) \). Optimal adoption time is driven by characteristics of the product and the physician population, such as the ease of learning and the physician’s ability to learn from peers. For example, if the physician adopts too early, his average clinical results during the new PPI generation’s time on the market would be lower than his historical clinical results. Although this is the case, there is also clear benefit for the physician to adopt the new product update at a later time. Given the appropriate \( \theta \) and \( \rho \), the average clinical results are certainly higher than the physician’s results prior to adoption when enough knowledge has been amassed by his peers, and while there is still enough time left in the PPI’s lifecycle for it to be worthwhile to adopt and learn. This benefit can be inflated by less frequent product updates and longer periods where product versions overlap, which correlates to higher values of both \( \theta \) and \( \rho \).

Ninety-nine percent of the trials in the full-factorial experiment resulted in at least one pure Nash equilibrium, each of which is comprised of predicted actions, as well as predicted payoffs, for both players. In the following sections, the general classes of payoffs across these trials are considered in detail. The remaining 1% of trials are excluded from subsequent analysis.

4.2.2 Understanding Expected Payoffs
To compare the players’ expected utility across trials, the predicted payoffs for the top-Pareto-ranked Nash equilibria were first normalized across all trials and all actions. To accomplish this, we found the maximum and minimum payoff values for the full-factorial experiment and normalized the payoff values between 0% to 100% corresponding to the minimum and maximum values, respectively. For example, if the minimum value was identified to be 0 and the maximum value was found to be 195, then a \( u_2 \) value of 100 is equal to a normalized value of \( 100/(195-0) \), or 51%. It is worth noting that \( R(0) \), the starting point of the physician’s clinical results prior to adoption of a new PPI generation, is set equal to a value of 100 (normalized to 51%) for all trials.

Then, the top-ranked Nash equilibria (each of which is represented by a normalized \( u_1, u_2 \) pair) were plotted as shown in the Figure 25. The size of the bubbles in this figure correlates with the frequency that each combination of normalized \( u_1 \) and \( u_2 \) values occurred as the top-Pareto ranked outcome. This diagram clearly indicates five classes of behavior present in the top-ranked outcome. In Class 1, the physician achieves a moderate payoff at or around the current clinical results, which occurs at a normalized value of 51%. In Class 1, the manufacturer only receives a minimal gain. In Class 2, both the physician and the manufacturer achieve a moderate payoff. In Classes 3, 4, and 5, the manufacturer achieves excellent payoff, while the physician’s payoff is moderate, strong, and excellent, respectively. Numeric ranges used to categorize these five classes are summarized in Table 16, below. The red boxes in Figure 25 correspond to the ranges defined in Table 16.
Table 16: Payoff Class Ranges

<table>
<thead>
<tr>
<th>Payoff Class</th>
<th>Range for Normalized $u_1$</th>
<th>Range for Normalized $u_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$40% \leq u_1 &lt; 60%$</td>
<td>$0% \leq u_2 &lt; 20%$</td>
</tr>
<tr>
<td>2</td>
<td>$60% \leq u_1 &lt; 80%$</td>
<td>$50% \leq u_2 &lt; 90%$</td>
</tr>
<tr>
<td>3</td>
<td>$90% \leq u_1 &lt; 100%$</td>
<td>$60% \leq u_2 &lt; 80%$</td>
</tr>
<tr>
<td>4</td>
<td>$90% \leq u_1 &lt; 100%$</td>
<td>$80% \leq u_2 &lt; 90%$</td>
</tr>
<tr>
<td>5</td>
<td>$90% \leq u_1 &lt; 100%$</td>
<td>$90% \leq u_2 &lt; 100%$</td>
</tr>
</tbody>
</table>

In addition to depicting five major classes of payoff outcomes, this diagram also demonstrates the physician’s advantage in the product update game. Under some scenarios, it is clear that the manufacturer cannot expect to receive a high payoff. Despite the manufacturer’s outcome, in almost all cases, the physician will be no worse off than he started, and in many cases, his average clinical results will improve.

Finally, we can see from this diagram that there is a positive correlation between $u_1$ and $u_2$. When the manufacturer’s outcome is improved, the physician’s is as well. Although it is not directly modeled within
the PPI product update game, this correlation indicates that there is incentive within the PPI update game for the manufacturer and physician to work together for their mutual benefit. This finding suggests that there may be value in investigating the relationship further within the framework of a cooperative game. Further, policy makers should be aware of the mutually beneficial relationship and seek to understand its effects within the context of any policy development activities. It is important to note that this mutually beneficial relationship between the manufacturer and the physician may be of great benefit to the patient population, as well. This is driven by the specific type of value that the new PPI generation addresses. For example, if the product update reduces the procedure time for physician and his team in the operating room, the patients may have little to gain by the update. Conversely, if the product update adds value by reducing the recovery time, then the patients, as well as the manufacturer and physician, have much to gain from the adoption of the new PPI generation.

4.2.3 Differentiating between Payoff Classes
In order to understand the physician and manufacturer characteristics that delineate the expected payoff classes, the C4.5 algorithm was applied using the model input parameters as attributes, as described in Section 4.1. For each of the 1,506 trials which resulted in one or more pure Nash equilibria, the top-Pareto-ranked outcomes were classified. This classification yields the decision tree in Figure 26. All trials are classified correctly when applying the decision tree that results from the C4.5 algorithm. Nearly seventy-six percent of the experimental trials are represented by only two classes (Payoff Classes 1 and 5).

Figure 26: Payoff Class Decision Tree
The decision tree shows that the maximum clinical product value achievable by the adopting physician, $V(\theta_{max})$, is a key characteristic which distinguishes between payoff classes. With a low maximum clinical value, both the manufacturer and physician can expect to find themselves in the lowest possible payoff class. However, given a high maximum clinical value, the physician’s loyalty, or likelihood of switching to a competing manufacturer, is a distinguishing characteristic. When the physician population is highly likely to switch to another manufacturer due to innovation in the marketplace ($S(\theta) = $ Option 3), the gains for both players during a single product generation’s lifetime are moderate, at best. But, when the physicians are only moderately impacted by either very frequent updates or very infrequent updates, or if they are quite sensitive to frequent updates ($S(\theta) = $ Option 1 or Option 2, respectively) will be excellent and the physician will have moderate to excellent improvement in clinical results.

We also see from our results that for the manufacturer to achieve a high payoff function (payoff classes 3, 4, and 5), the optimal $\theta$ is either moderately high, or high. However, if the maximum product value is low, the manufacturer will not benefit from developing a new product generation. Under this low-value scenario, the physician’s expected payoff will be near his starting point ($R(0))$. The role of the maximum clinical product value, $V(\theta_{max})$, is investigated further in Section 4.2.4.

We began the manufacturer-physician model with the hypothesis that the average physician’s capacity to learn creates an upper bound on the spread of a new PPI product generation through the physician population, which increases $\theta$. Given a high product value and less sensitivity to infrequent updates ($S(\theta) = $ Option 1 or Option 2), we see that the players’ success is driven by the characteristics of physician learning. This supports the hypothesis that the physician’s learning limits the optimal $\theta$. The physician’s capacity to learn is represented by the learning curve from which his payoff function is derived, while the manufacturer’s payoff function represents the “spread” of the new product generation. We see in the results that both players can expect the best payoffs (Payoff Class 5) if the new product generation can be learned quickly. This corresponds to two possible scenarios: either 1) the new generation requires a low value of $L$ (the number of procedures the physician will require to master the new generation) or, 2) the new generation requires a high value of $L$ and the physician experiences a high volume of demand for the procedure (a high value of $P$).

4.2.4 Product Value

Experimental results in Section 4.2.3 indicated that product value plays a key role in distinguishing between scenarios in which the manufacturer has either very strong or very weak payoff results. To further investigate this phenomenon, we consider only the trials which are classified into payoff class 1 or 5, covering 75% of the full-factorial input scenarios. With only these trials, the classification algorithm is
applied again, resulting in the decision tree in Figure 27.

![Decision Tree Image]

**Figure 27: Simplified Payoff Class Decision Tree**

This decision tree shows that only the maximum improvement in clinical value, \( V(\theta_{max}) \), is a factor in determining the classification of trials into the two major classes that exist in the payoff space. To gain further insights into the effects of product value, we performed a second full-factorial experiment. In this experiment, all model input parameters that were not a factor in this simplified decision tree are fixed, and more levels are introduced for \( V(\theta_{max}) \). Table 17 summarizes the new levels used for the factors, while other parameters remain fixed as described earlier in Table 10. These new factor levels resulted in 10 trials.

<table>
<thead>
<tr>
<th>Table 17: Factor Levels for Focused Experiment</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Factor</strong></td>
</tr>
<tr>
<td>Probability of Switching</td>
</tr>
<tr>
<td>Adoption Time Distribution</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Product Value</td>
</tr>
<tr>
<td>Physician Learning</td>
</tr>
<tr>
<td></td>
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<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>
The payoffs from the top-ranked outcomes of these ten trials were normalized across the same range that was used to normalize the original full-factorial experiment, for ease of comparison to the original results. The normalized payoffs for these ten new trials are depicted in Figure 28. In this figure, the diamond-shaped endpoints indicate the results that were observed in the original experiment. As the maximum value increases, $u_1$ grows at a much higher rate than $u_2$. This suggests that the manufacturer’s results are more sensitive to the product value than the physician.

![Figure 28: Normalized Payoff Functions Across $V(\theta_{max})$](image)

Figure 29 depicts the normalized payoff pairs relative to the five payoff classes identified in the original full-factorial experiment. We see from these results that when all other parameters were held constant, the payoff class was dramatically affected by the maximum achievable product value. In other words, the $u_1$ and $u_2$ are highly sensitive to $V(\theta_{max})$. Also, the product generation value has a positive correlation with the physician’s and manufacturer’s results. This correlation supports our earlier observation that both the manufacturer and the physician may benefit from a cooperative partnership. The omission of cost from the physician’s PPI decision making process may remove a disincentive for the manufacturer to increase the value (i.e., innovation), and corresponding cost, of the new PPI generation. This motivates consideration of the role of a third player, such as the hospital, in cost control efforts which can work against innovation.
4.2.5 Actions at Equilibria

Finally we want to understand the relationship between the Nash equilibria actions and payoffs. To accomplish this, first the players’ action spaces were segmented into action groups. Then, the action groups were mapped to the payoff classes (see Table 16) in order to identify how the different types of player decisions correlate to the expected player payoffs.

To categorize the trials into groups with similar actions, the possible values for each decision variable \((\theta, \rho, \omega)\) were categorized as being low (L), moderate (M), or high (H) in value. This assignment is distributed evenly across the possible decision variable values, as shown in Table 18. Then, these categories were used to partition the action space into 27 zones, each of which corresponds to a combination of decision variable categories. An example of one of these combinations is (L, M, H), which equates to a low value for \(\theta\), a moderate value for \(\rho\), and a high value for \(\omega\). The ranges used to partition each of the three dimensions of the action space are given in Table 18.

Following this, the actions predicted by the top Pareto-ranked Nash equilibria for each trial were mapped to the action space zones. Although 27 \((3^3)\) zones are present in the action space partition, the top-ranked equilibria occurred in only five of the zones. Based upon the frequency of these occurrences, the following four action groups were identified: Action group 1 corresponds to high values of \(\theta\) and \(\rho\), with a low value of \(\omega\). Action group 2 is defined as a moderate value of \(\theta\), a high value of \(\rho\), and a low value of \(\omega\). Action group 3 translates to high values for all three decision variables. Finally, action group 4 is the
remainder of observed actions, including several trials which resulted in two pure Nash equilibria with tied rankings. A summary of the distribution of trials across these four action groups is provided in Table 19. The relationship between these optimal action groups and their associated payoff classes can be seen in Figure 30.

Table 18: Categorizing Decision Variable Values

<table>
<thead>
<tr>
<th>Category</th>
<th>$\theta$</th>
<th>$\rho$</th>
<th>$\omega$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low (L)</td>
<td>3-24 months</td>
<td>0-16 months</td>
<td>1-16 months</td>
</tr>
<tr>
<td>Moderate (M)</td>
<td>24-48 months</td>
<td>16-32 months</td>
<td>16-32 months</td>
</tr>
<tr>
<td>High (H)</td>
<td>48-72 months</td>
<td>32-48 months</td>
<td>32-48 months</td>
</tr>
</tbody>
</table>

Table 19: Frequency of Action Groups

<table>
<thead>
<tr>
<th>Action Group</th>
<th>Action Partition</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (Blue)</td>
<td>(H, H, L)</td>
<td>960 trials (64%)</td>
</tr>
<tr>
<td>2 (Green)</td>
<td>(M, H, L)</td>
<td>436 trials (29%)</td>
</tr>
<tr>
<td>3 (Red)</td>
<td>(H, H, H)</td>
<td>62 trials (4%)</td>
</tr>
<tr>
<td>4 (Yellow)</td>
<td>(M, M, L), or (H, H, L) and (H, H, H), or (M, M, M) and (H, H, H)</td>
<td>48 trials (3%)</td>
</tr>
<tr>
<td>Total:</td>
<td></td>
<td>1506 (100%)</td>
</tr>
</tbody>
</table>

Figure 30: Normalized Top Ranked Payoffs with Action Groups
Figure 30 depicts the frequency that each action group occurs for each expected payoff result. From inspecting the relationships between the optimal action groups and the expected payoff classes, some interesting results can be observed. We see that actions which result in high expected payoffs under some conditions may result in low expected payoffs under other conditions. From the results presented in 4.2.2, we know that the maximum achievable product value differentiates between payoff class 1 and payoff class 5. So, even if players select the equilibria actions for payoff class 5, they will not obtain the expected class 5 payoffs unless the characteristics of the product (specifically $V(\theta_{\text{max}})$) are not ideal. This can also be seen with action groups 2 and 4, which sometimes result in class 1 payoffs, and in other scenarios, they result in payoff class 2, 3, or 4. In the original full-factorial experiment results, only action group 3 resulted in consistent payoffs. In other words, high values for all three decision variables, while optimal under some conditions, are never observed to result in even moderate gains for either player. In fact, in some scenarios corresponding to action group 1, the physician will experience average clinical results lower than the point at which he started. Given the manufacturer’s upper-hand in controlling many defining characteristics, such as the maximum achievable clinical value ($V(\theta_{\text{max}})$), the initial drop in physician results after adopting the new PPI generation ($D(0)$), and the number of procedures required by the average physician to achieve the maximum results ($L$), it is clear that the manufacturer should carefully consider their decisions that can affect these parameters. Likewise, within the context of the product-update game, it is in the physician’s best interest to have large $P$ values.

4.3 Sales Rep Game Results

Using the numerical values defined in Section 3.2.6.2, the values for the payoff functions, $u_1$ and $u_2$, were calculated for each combination of player strategies in the action space in order to generate a normal form representation for each trial. Using the approach described in Section 4.1, the following results are discussed below: 1) General form of payoffs 2) Classification of payoffs, 3) Impact of sales rep effectiveness input parameters, and 3) Relationships observed between predicted actions and payoffs.

4.3.1 General Behavior of Game

The full-factorial experiment defined 1,680 normal form games, and generated 13,506 values for both $u_1$ and $u_2$ per game. To understand how these effects materialize across the player action space, we consider the form of the payoff functions of a single trial here. Figures 23 and 24 depict $u_1$ and $u_2$, respectively, calculated from the input parameter values given in Table 20.
Table 20: Factor Levels for Example Payoffs

<table>
<thead>
<tr>
<th>Factor</th>
<th>Factor Description</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability of Switching</td>
<td>( S(\theta) )</td>
<td>Defines the probability of switching as a function of the product update interval ( (\theta) )</td>
</tr>
<tr>
<td></td>
<td>( S(\theta_{\text{max}}) )</td>
<td>Probability of switching manufacturers when ( \theta = \theta_{\text{max}} )</td>
</tr>
<tr>
<td>Adoption Time Probability Distribution</td>
<td>( \lambda_1 )</td>
<td>Shape parameter for adoption time probability distribution function</td>
</tr>
<tr>
<td>Product Value</td>
<td>( V(\theta) )</td>
<td>Clinical value of new product generation as a function of the product update interval ( (\theta) )</td>
</tr>
<tr>
<td></td>
<td>( V(\theta_{\text{max}}) )</td>
<td>Clinical value of new product generation when ( \theta = \theta_{\text{max}} )</td>
</tr>
<tr>
<td>Physician Learning</td>
<td>( L )</td>
<td>Number of procedures for physician to achieve maximum product value</td>
</tr>
<tr>
<td></td>
<td>( q )</td>
<td>Constant relating ( D ) and ( \omega ), representing peer learning</td>
</tr>
<tr>
<td></td>
<td>( a )</td>
<td>Sales rep gain factor; Reduction of ( L ) produced by sales rep-provided training</td>
</tr>
<tr>
<td></td>
<td>( D(0) )</td>
<td>Percent drop of physician’s clinical results if adoption occurs when ( t = 0 )</td>
</tr>
<tr>
<td></td>
<td>( p )</td>
<td>Number of patients physician sees each month</td>
</tr>
</tbody>
</table>

The Nash equilibrium for this trial occurs at the actions \( \theta = 21 \) months, \( \rho = 18 \) months, and \( \omega = 8 \) months, and it is indicated by red arrows in Figures 31 and 32.

The contour plot given in Figure 31 shows \( u_1 \) for the selected trial. The contour along the \( A_z \) dimension is driven by the adoption time distribution, as it was in the original model. As the physician selects a smaller value of \( \omega \), the proportion of physicians adopting before \( \rho \) increases. As before, each of the groupings in the \( A_1 \) dimension corresponds to a value of \( \rho \), within which the \( \theta \) increases. We see in this trial that the manufacturer benefits from low physician adoption times. As in the original model, the manufacturer’s benefit from early adoption times, but this effect is diminished as the rollover policy becomes less restrictive to the physician.

One notable difference between this trial and the behavior observed in the original game is that when the manufacturer uses higher values of \( \theta \), the payoff is reduced. In Figure 17, we observed that as \( \theta \)
increased, $u_1$ also increased. However, in this particular trial $u_1$ decreases as $\theta$ increases. This suggests that there are cases when a manufacturer would have an incentive to push for frequent product updates. We see this result under the conditions stated in Table 20, which capture the scenario of an R&D process that has diminishing impact upon the product value over time, and a physician population that becomes more likely to switch to a competitor’s product over time.

![Figure 31: Manufacturer’s Payoff for Selected Trial](image)

In the second contour plot (Figure 32), $u_2$ is given for the trial described in Table 20. In this figure, we see that $u_2$ “falls off a cliff” when $\omega > \rho$, as it did in the first game. As in the original model, $u_2$ reaches its highest point where the tradeoff between peer learning and product value is optimal. As $\theta$ increases, $u_2$ increases, in both the original and in the Sales Rep Game. Unlike the first game, where the physician’s benefit of less frequent updates is shared by the manufacturer, the manufacturer would prefer more frequent updates under this particular sales rep scenario. While the manufacturer would prefer the minimum value for $\theta$, and the physician would prefer the maximum, we see that $\theta^*$ from the Nash equilibrium occurs at a moderate value ($\theta = 21$ months), providing a compromise between the two players.
As with game I, additional figures that depict each player payoff as a function of the player decisions \((\theta, \rho, \text{ and } \omega)\) are provided in Figures 33-38. In Figures 33 and 34, \(u_1\) is shown as a function of \(\theta\), while another player decision (\(\rho\) or \(\omega\)) is shown at several levels, and the remaining player decision is held constant. In both of these figures, an immediate jump in \(u_1\) is apparent when \(\theta \geq \rho\). This is not unlike the form seen in similar figures for the original Manufacturer-Physician model. However in the original model, \(u_1\) increased after the initial jump, and in the Sales Rep model, a drop-off in results begins immediately. This is due to the combined effects of the probability of switching \((S(\theta))\) and the product value \((V(\theta))\), both of which are modeled as functions of \(\theta\).

The next two charts, Figures 35 and 36, also depict \(u_1\), this time as a function of \(\rho\). As with the first game, these figures demonstrate that \(u_1\) is proportional to \(\rho\). Unlike the original game, here we see that \(u_1\) is not necessarily increasing as \(\rho\) increases. In fact, Figure 35 clearly shows that for higher values of \(\theta\), \(u_1\) does not reach the same levels as possible with lower values of \(\theta\). However, the lowest possible \(\theta\) also does not result in the highest possible \(u_1\). This suggests that a tradeoff in \(\theta\) exists under the more complex loyalty and product value relationships present in the Sales Rep formulation. As in the first game, we see that the curves associated with lower values of \(\theta\) are truncated. This is driven by the
restriction put in place in both games which prevents more than two product generations being on the market at any point in time. (This restriction is achieved by setting \( u_1 = 0 \) for any instances when \( \rho \geq \theta \).) Figure 36 demonstrates this truncation, which occurs when \( \rho \) reaches 36 months and becomes equal to \( \theta \). Figure 36 also demonstrates a direct tie between the \( \omega \) and \( u_1 \). Interestingly, in this particular trial, we see that the manufacturer is able to reach its highest payoff even with a later \( \omega \), if \( \theta \) is properly selected.

Finally, Figures 37 and 38 show \( u_2 \) as a function of \( \omega \). In Figure 37, several values of \( \theta \) are shown and \( \rho \) is held constant. In Figure 38, several rollover policy decisions are shown, and \( \theta \) is held constant. In these figures, we see that \( u_2 \) in the Sales Rep game has a very similar form as in the original Manufacturer-Physician game. As in the original game, the maximum payoff occurs after some time has passed, which is due to the benefit gained by waiting to adopt until a certain amount of peer learning is achieved. As in the first game, an immediate drop-off in results takes place if \( \omega > \rho \).

Like the example trial discussed in Figures 33-38 above, most trials in the Sales Rep Game resulted in at least one pure Nash equilibrium. Out of 1,680 trials, 33 resulted in no pure Nash equilibrium. As detailed in Section 3.2.2, this occurs when the players’ payoff functions lead to a scenario in which each player’s strategy is relies upon “outguessing” the other player (Gibbons 1992). In the next sections, all 1,647 trials which did result in one or more pure Nash equilibria are grouped into general classes of results with similar payoff outcomes. These payoff classes are further analyzed in order to provide insights into the sales rep’s impact upon the PPI supply chain.

Figure 33: Manufacturer’s Payoff Across \( \theta \) (Constant \( \omega \))
Figure 34: Manufacturer's Payoff Across $\theta$ (Constant $\rho$)

Figure 35: Manufacturer's Payoff Across $\rho$ (Constant $\omega$)
Figure 36: Manufacturer’s Payoff Across $\rho$ (Constant $\theta$)

Figure 37: Physician’s Payoff Across $\omega$ (Constant $\rho$)
4.3.2 Understanding Expected Payoffs

The Nash equilibria resulting from 1,647 Sales Rep trials were classified in accordance with the process described in Section 4.1. The payoffs associated with the top-ranked Nash equilibria for each trial were normalized across all Nash equilibria that resulted from the trials, in order to compare results across trials. This normalization results in a range of normalized payoff values between 0% and 100%. However, in the Sales Rep Game, the range of physician’s payoffs are significantly higher than the payoffs observed in the original model’s results. Adjusting for the normalized scale, the initial starting value for physician clinical results ($R(0) = 100$) is equivalent to a normalized payoff value of 50%.

Although the normalized payoff values are used for analyzing which supply chain characteristics result in the different classes of payoff outcomes, it is worth noting the relative magnitudes in payoffs between the original Manufacturer-Payoff game and the Sales Rep Game. In the original model, the manufacturer’s top-ranked payoffs ranged from 0.005 to 0.863 and the physician’s top-ranked payoffs ranged from 80.5 to 194.8. However, in the Sales Rep Game, the manufacturer’s top-ranked payoffs ranged from 0.002 to 1.000 and the physician’s top-ranked payoffs ranged from 87.8 to 199.0. The magnitude of both players’ payoff functions improves in the second model, which suggests that both parties may benefit by leveraging the relationship between each other with a sales rep. In later sections, we find that the instances with a significantly higher magnitude for the manufacturer occur with increased physician loyalty.
As with the original model results, the top-ranked Nash equilibria, represented by a normalized $u_1$, $u_2$ pair, were plotted as shown in the Figure 39. The size of the bubbles in this figure depicts the frequency that each combination of normalized $u_1$ and $u_2$ values occurred as the top-Pareto ranked outcome. As before, these top-ranked outcomes are grouped into five classes of similar behavior. In Class 1, the physician achieves a moderate payoff slightly above his current clinical results, and the manufacturer only receives a minimal payoff. In Class 2, both the physician and the manufacturer achieve a moderate payoff. In Class 3, the manufacturer’s payoff improves over Class 2 while the physician’s results do not. Class 4 results are strong for both the manufacturer and physician, and in Class 5 both players achieve outstanding results. Numeric ranges used to categorize these five classes are summarized in Table 21, below, and the red boxes in Figure 39 correspond to these ranges.

Table 21: Payoff Class Ranges

<table>
<thead>
<tr>
<th>Payoff Class</th>
<th>Range for Normalized $u_1$</th>
<th>Range for Normalized $u_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$0% \leq u_1 &lt; 15%$</td>
<td>$0% \leq u_2 &lt; 75%$</td>
</tr>
<tr>
<td>2</td>
<td>$15% \leq u_1 &lt; 30%$</td>
<td>$45% \leq u_2 &lt; 85%$</td>
</tr>
<tr>
<td>3</td>
<td>$30% \leq u_1 &lt; 40%$</td>
<td>$55% \leq u_2 &lt; 85%$</td>
</tr>
<tr>
<td>4</td>
<td>$65% \leq u_1 &lt; 75%$</td>
<td>$50% \leq u_2 &lt; 90%$</td>
</tr>
<tr>
<td>5</td>
<td>$85% \leq u_1 &lt; 100%$</td>
<td>$75% \leq u_2 &lt; 100%$</td>
</tr>
</tbody>
</table>

Figure 39: Payoff Classes
From Figure 39 we see that the physician still has the advantage in this game. Despite the manufacturer’s outcome, the average physician will nearly always achieve clinical results that improve upon his initial clinical result ($R(0) = 100$) prior to adopting the new product generation. Like the original Manufacturer-Physician game (with no sales rep), there is a strong correlation between the physician’s success and the manufacturer’s success. Due to the even higher clinical results in this model, the patients are even better off than before, as long as the clinical results improved by the new product generation are relevant to the patient, and not just the physician. However, it is important to note that there is more spread in the physician results across each class than observed in the original model. This can be partially attributed to the additional product value shapes which are used in the Sales Rep formulation. However, the effectiveness of the sales rep, modeled here by both the sales rep gain factor ($\alpha$) and the probability of switching ($S(\theta)$), also impact these payoff results. The effects of these sales rep effectiveness factors are investigated further in Section 4.2.3.

4.3.3 Differentiating between Payoff Classes

Following the method described in Section 4.1, the trials from the Sales Rep game were classified using the C4.5 supervised learning algorithm. The resulting decision tree is shown in Figure 40. Additional details from the classification algorithm results are in Appendix D. Like the original PPI supply chain game results, the majority of the trials fell into either Payoff Class 1 or 5.

![Figure 40: Payoff Class Decision Tree](image-url)
Not surprisingly, several outcomes from the Sales Rep experiment are quite similar to those from the original PPI supply chain game. Figure 40 shows that the maximum clinical product value achievable by the adopting physician, $V(\theta_{max})$, is a key characteristic which distinguishes between the five classes of outcomes. Here again, with small values of $V(\theta_{max})$, both the manufacturer and physician can expect to find themselves in the lowest possible payoff class. Also similar to the original game, we see here that even with high values of $V(\theta_{max})$, the physician’s loyalty, or likelihood of switching to a competing manufacturer, is again a key distinguishing characteristic.

Assuming that the new product generation has a large $V(\theta_{max})$, all five possible payoff class outcomes are still plausible, and the resulting payoff class is primarily driven by characteristics of the physician’s loyalty. If the manufacturer’s sales rep-based approach is so effective that the physicians are unlikely to switch their preferences to a competing manufacturer ($S(\theta_{max})$ is low) then both the manufacturer and physician will experience outstanding results (Class 5). Surprisingly, even if the physician population is highly likely to switch to another manufacturer given a long time between new product generations ($S(\theta_{max})$ is high), a relatively strong outcome is feasible. Results indicate that Class 4 can be obtained if the sales reps are able to postpone the physician’s decision to switch manufacturer, and the R&D process can obtain some key product value gains in a shorter cycle. (This scenario is represented in the game when $S(\theta)$ has the “accelerated”, or convex shape, and $V(\theta)$ has the “diminishing returns”, or concave shape.) In fact, if the manufacturer is not able to maintain a small $S(\theta_{max})$ given a long development cycle, they will still be better off if the sales reps can postpone the physician’s decision to switch. We see this in Figure 40, where, given a high probability of switching at $\theta_{max}$, the payoff class with an “accelerated” switching curve is always higher than with an “immediate” shape.

These results suggest that the manufacturer’s product development strategy should aim for high product value and a sales rep-based strategy that drives long-term physician loyalty. If successfully executed, this approach should result in outstanding results (Payoff Class 5) as shown in Figure 40. If long-term physician loyalty is not achievable, then the manufacturer should focus on having a product development strategy that seeks out the “low-hanging fruit” for improving the product as quickly as possible, with the largest results. (In Figure 40, this corresponds to the node in which $V(\theta)$ has the “diminishing returns” shape.) However, this R&D approach will only be beneficial if the lack of sales rep performance, or another reason (such as the product falling short of physician expectations), does not induce immediate physician brand preference changes, and the sales reps are able to convince the physicians to postpone their decision to switch manufacturers ($S(\theta)$ has the “accelerated” shape).
4.3.4 Sales Rep Gain Factor

The payoff classification in Section 4.3.3 resulted in five payoff classes that had distinct manufacturer payoff results, but the physician payoff results were somewhat overlapped across the five classes. To further investigate the effects of the sales rep upon the payoff results, we consider additional values of the sales rep-related model parameters in a smaller experiment. Input values used for this experiment are summarized in Table 22.

Table 22: Factor Levels for Focused Experiment

<table>
<thead>
<tr>
<th>Factor</th>
<th>Factor Description</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability of Switching</td>
<td>( S(\theta) ) Defines the probability of switching as a function of the product update interval (( \theta ))</td>
<td>100% Loyalty, Immediate, or Accelerated (as shown in Figure 11)</td>
</tr>
<tr>
<td></td>
<td>( S(\theta_{max}) ) Probability of switching manufacturers when ( \theta = \max \theta )</td>
<td>100%</td>
</tr>
<tr>
<td>Adoption Time Probability Distribution</td>
<td>( \lambda_1 ) Shape parameter for adoption time probability distribution function</td>
<td>4</td>
</tr>
<tr>
<td>Product Value</td>
<td>( V(\theta) ) Clinical value of new product generation as a function of the product update interval (( \theta ))</td>
<td>Diminishing Returns (as shown in Figure 12)</td>
</tr>
<tr>
<td></td>
<td>( V(\theta_{max}) ) Clinical value of new product generation when ( \theta = \max \theta )</td>
<td>10%</td>
</tr>
<tr>
<td>Physician Learning</td>
<td>( L ) Number of procedures for physician to achieve maximum product value</td>
<td>75 procedures</td>
</tr>
<tr>
<td></td>
<td>( q ) Constant relating ( D ) and ( \omega ), representing peer learning</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td>( a ) Sales rep gain factor; Reduction of ( L ) produced by sales rep-provided training</td>
<td>0% to 90%, in increments of 10%</td>
</tr>
<tr>
<td></td>
<td>( D(0) ) Percent drop of physician’s clinical results if adoption occurs when ( t = 0 )</td>
<td>10%</td>
</tr>
<tr>
<td></td>
<td>( p ) Number of patients physician sees each month</td>
<td>1 patient</td>
</tr>
</tbody>
</table>

The payoffs from the top-ranked outcomes of these trials are normalized across the same range that was used to normalize the original full-factorial experiment. The normalized physician payoffs for the new trials are plotted in Figure 41 as a function of the sales rep gain factor (\( a \)). The colors in this figure are used to indicate which of the three probability of switching forms the physician’s outcomes are associated with. Scenarios with a sales force that is able to drive 100% physician loyalty (\( S(\theta) = 0 \forall \theta \)) are indicated in blue, while the cases of a sales rep having negative effects on physician loyalty (\( S(\theta) \) has the “immediate” shape) are indicated in green. Finally, results associated with the scenario of decreasing
Figure 41 indicates that the physician’s payoff will improve as the sales rep’s ability to provide training (α) increases. Interestingly, though, we see here that the shape of the switching probability curve has a greater effect on the physician’s payoff results than the sales rep gain factor. While at first it may seem counterintuitive that the physician’s loyalty to the manufacturer provides a greater impact to his payoff function than does the sales rep gain factor, this result is expected due to the critical role of product value. If a higher product value can be gained with a longer product development cycle, and if the manufacturer does not perceive a threat of losing physicians to competitors by selecting a longer product development cycle, then both the manufacturer and physician will experience greater results due to a higher product value.
In Figure 42, we see that $u_1$ is constant across all values of $\alpha$, indicating that the sales rep’s training effectiveness does not directly impact the manufacturer’s results. However, we see in Figures 41 and 42 that the sales rep’s training effectiveness (as represented by $\alpha$) does provide some benefit to the physician. This is indicated by the positive slopes of the physician payoff curves in Figure 41, and the spread of the physician payoff results within each payoff class in Figure 42. Although these results suggest that the sales rep’s ability to train the physician does not directly impact $u_1$, it is important to note that in the formulation for this work, the sales rep’s training effectiveness was not linked to his or her ability to positively impact physician loyalty. In reality, if the sales rep’s ability to train physicians would enhance or improve physician loyalty, the sales rep’s ability to train would be a key factor in determining $u_1$ as well as $u_2$.

This experiment indicates that the physician’s loyalty to a manufacturer enables the manufacturer to select $\theta$ and $\omega$ values that improve $u_1$ and $u_2$. If the sales rep’s ability to provide valuable training to the physician drives loyalty, then it is a key determinant in the results of both parties. Given this, the
manufacturer’s sales rep strategy should focus on enabling sales reps to become adept at determining what drives the loyalty of each physician. This is not contrary to providing effective training to the physician; if the sales rep provides indispensable training and support for the physician, thus increasing loyalty, then both parties clearly benefit. From the physician’s point of view, a good strategy would be to seek out a manufacturer that provides excellent training and product value, and offer clear signals to the manufacturer’s sales rep about the characteristics of the relationship that impact his personal loyalty to the manufacturer’s brand.

4.3.5 Actions at Equilibria
Results discussed in Section 4.3.4 indicate that while the training effectiveness of the sales rep is beneficial to the physician, the ability of the sales rep to generate physician loyalty drives the manufacturer’s payoff. In the mechanics of this formulation, this is driven by the shape and the magnitude of the probability of switching curve, which is directly impacted by the success of the manufacturer’s sales rep approach. To investigate the impact of the manufacturer’s sales rep approach upon its optimal product update interval, we analyze the relationship between the Nash equilibria actions and payoffs.

This analysis was performed by applying the procedure described in Section 4.1 to all trials in the Sales Rep Game full-factorial experiment described in Section 3.2.6.2 that resulted in one or more pure strategy Nash equilibria. As in the original model, the players’ action spaces were segmented into a partition across the players’ action space (Table 18). Then, the observed segments were categorized into action groups. The action groups were subsequently mapped to the payoff classes in order to identify how the different types of player decisions correlate to the expected player payoffs.

Based upon the frequency that each action partition occurred, as shown in Table 23, the following three action groups were defined: Action group 1 corresponds to high values of $\theta$ and a low value of $\omega$. Action group 2 is defined as a moderate value of $\theta$, and a low value of $\omega$. Finally, action group 3 translates to low values for both $\theta$ and $\omega$. Unlike the results from the original Manufacturer-Physician model, a negligible amount of results ($\leq 20$ trials) were associated with high values of $\omega$. Action groups 1 and 2 are somewhat similar in both the original Manufacturer-Physician Game and the Sales Rep Game (action group 1 for both models ties to a high value of $\theta$ and a low value of $\omega$, and action group 2 for both models are associated with a moderate value of $\theta$ and a low value of $\omega$). However, in general, the action groups of the two models are comprised of differing partitions, and therefore are not directly comparable. In fact, results from the Sales Rep Game include 197 trials for which a low value of $\theta$ is optimal (action group 3), while none of the trials tested in the original model resulted in a low value for the optimal product update interval. The relationship between these optimal action groups and their associated payoff classes can be seen in Figure 43.
Table 23: Frequency of Action Groups

<table>
<thead>
<tr>
<th>Action Group</th>
<th>Action Partition</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (Blue)</td>
<td>(H, H, L)</td>
<td>1,116 trials (66%)</td>
</tr>
<tr>
<td>2 (Green)</td>
<td>(M, H, L) or (M, M, L)</td>
<td>314 trials (19%)</td>
</tr>
<tr>
<td>3 (Red)</td>
<td>(L, L, L) or (L, M, L)</td>
<td>197 trials (12%)</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>1,627 trials (100%)</td>
</tr>
</tbody>
</table>

Figure 43: Normalized Top Ranked Payoffs

Figure 43 depicts the frequency that each action group occurs for each payoff class that was defined in Section 4.3.2. From inspecting the relationships between the optimal action groups and the payoff classes, some interesting results can be observed. As in the original game, the same actions can result in a different payoff class under different conditions. For example, optimal strategies represented by action group 1 results in outstanding payoff results (Payoff Class 5) when the new product generation has a high value, but it is also optimal in some cases of the low-valued new product generation, which have relatively low payoff outcomes (Payoff Class 1).
Under certain scenarios, it becomes optimal for the manufacturer to release new product generations more frequently with sales reps in place, as hypothesized (Action Group 3 corresponds to a low value of $\theta$.) Frequent PPI updates were observed to be optimal for trials that resulted in several payoff classes. A frequent product update interval resulted when some significant product value was achieved quickly ($V(\theta)$ has concave “diminishing returns” shape), and:

- Achievable product value ($V(\theta_{max})$) is low
- Achievable product value ($V(\theta_{max})$) is high, the possible probability of switching ($S(\theta_{max})$) was high, and physicians have a high probability of switching manufacturers.

This result supports the hypothesis that by providing a sales rep to train and assist the physician, the manufacturer would facilitate an earlier physician’s adoption of a new PPI generation and enable a more frequent release of new product generations, at least under certain conditions: Updating PPI more frequently was observed to be optimal within the Sales Rep Game only when the manufacturer has the ability to obtain significant product value quickly ($V(\theta)$ has concave “diminishing returns” shape).

However, in order to achieve more desirable outcomes (Payoff Classes 2-5), the achievable product value must be high. In these cases, physician loyalty becomes a distinguishing characteristic between higher and lower payoff results. Within a given payoff class, it is clear that the physician will benefit when working with a sales rep that provides effective training for new PPI generations. Therefore, when faced with the option between two PPI brands with equivalent product value, it is in the physician’s best interest to select the brand which provides the most effective training. This indicates that providing effective training via sales reps for the physician may an important aspect of garnering physician loyalty. This, coupled with the importance of the physician loyalty in the outcome of the game, suggests that the success of the manufacturer’s sales rep-based strategy is a key characteristic that enables fast-paced releases of new PPI generations. Despite this result, it remains that both the manufacturer and physician could expect to be better off if 1) a less-frequent product update interval was selected because a significant improvement in product value could be realized with the release of the product update, and 2) the manufacturer’s product and service warranted significant physician loyalty.

4.4 Hospital Cost Control Game Results

Using the numerical values defined in Section 3.2.6.3 and the analysis approach described in Section 4.1, the full-factorial experiment defined 3,240 normal form games, after infeasible factor combinations were removed. Each trial generated 78,336 values for $u_1$, $u_2$ and $u_3$, across the 272x48x6 action space. The pure Nash equilibria were identified for each trial across these values. These Nash equilibria provide partial support for our initial hypothesis, which stated that when a PPI update provides a small clinical improvement, and the hospital implements a cost control policy to restrict adoption of the update, $\theta^*$ and $\omega$ both increase. Experiment results indicate that this hypothesis is partially supported. Further, results
indicate several key insights that can help hospitals make informed decisions about their cost control policies. Results from the experiment are discussed below via 1) the general form of the hospital’s payoff, 2) the classification of all player payoffs, 3) further investigation of specific trials, and 4) the relationship observed between predicted actions and their resulting payoffs.

4.3.1 General Behavior of Hospital Payoff

As an example of how the hospital’s payoff \( u_t \) varies across the action space, we consider this payoff function in the normal form representation of two trials here.

Both of these trials represent a scenario in which the average physician has minimal loyalty to the manufacturer, which decreases in an accelerated fashion as the time between product updates increases. Even though the average physician requires significant time to master the use of the new PPI, he expects to perform a very low volume of procedures requiring the PPI. However, he works with a very effective sales rep from the PPI manufacturer. In these cases, the physician has a low likelihood of diverting a portion of his procedures to another facility. Finally, in both of these selected these cases, the hospital places more emphasis on having cutting-edge clinical results than on cost control, and the manufacturer sets a price that accurately reflects the value of the new PPI generation (i.e., it is not under- or over-priced).

Although the two selected trials share these aspects of the PPI supply chain, they have different levels for their maximum product value. In Trial A, the manufacturer’s product development process is expected to incorporate attributes of the new PPI update that provide minimal additional product value \( V(\theta_{\text{max}}) = 10\% \), even given a long development period. In contrast, significant improvements to the product value are possible in Trial B \( V(\theta_{\text{max}}) = 100\% \). Input values which represent these two trials are summarized in Table 24.

Table 24: Factor Levels for Selected Trials

<table>
<thead>
<tr>
<th>Factor</th>
<th>Factor Description</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability of Switching</td>
<td>( S(\theta) ) Defines the probability of switching as a function of the product update interval ( \theta )</td>
<td>Accelerated (as shown in Figure 11)</td>
</tr>
<tr>
<td></td>
<td>( S(\theta_{\text{max}}) ) Probability of switching manufacturers when</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( \theta = \max \theta )</td>
<td>10%</td>
</tr>
<tr>
<td>Adoption Time Probability Distribution</td>
<td>( \lambda_1 ) Shape parameter for adoption time probability distribution function</td>
<td></td>
</tr>
<tr>
<td>Product Value</td>
<td>( V(\theta) ) Clinical value of new product generation as a function of the product update interval ( \theta )</td>
<td>Diminishing Returns (as shown in Figure 12)</td>
</tr>
<tr>
<td><strong>Clinical value of new product generation when $\theta = \max \theta$</strong></td>
<td><strong>10%</strong></td>
<td><strong>100%</strong></td>
</tr>
<tr>
<td>-----------------------</td>
<td>---------</td>
<td>---------</td>
</tr>
<tr>
<td>$V(\theta_{\text{max}})$</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Physician Learning</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$L$ Number of procedures for physician to achieve maximum product value</td>
<td>75 procedures</td>
<td></td>
</tr>
<tr>
<td>$q$ Constant relating $D$ and $\omega$, representing peer learning</td>
<td>0.1</td>
<td></td>
</tr>
<tr>
<td>$a$ Sales rep gain factor; Reduction of $L$ produced by sales rep-provided training</td>
<td>80%</td>
<td></td>
</tr>
<tr>
<td>$D(0)$ Percent drop of physician’s clinical results if adoption occurs when $t = 0$</td>
<td>10%</td>
<td></td>
</tr>
<tr>
<td>$p$ Number of patients physician sees each month</td>
<td>1 patient</td>
<td></td>
</tr>
<tr>
<td><strong>Weight of Clinical Results</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha$ Importance of clinical results to hospital</td>
<td>25%</td>
<td></td>
</tr>
<tr>
<td><strong>Claimed Value</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\bar{\phi}_{\min}$ Minimum claimed value of new product generation when $\theta = \max \theta$</td>
<td>10%</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Disparity between new generation’s actual value and claimed value</td>
<td>25%</td>
<td></td>
</tr>
<tr>
<td><strong>Probability of Switching Procedure Location</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$H(V(\theta_{\text{max}}))$ Probability of the physician switching to another hospital when $V(\theta) = V(\theta_{\text{max}})$</td>
<td>10%</td>
<td></td>
</tr>
</tbody>
</table>

The form of the hospital’s payoff for both Trial A and Trial B is depicted across the manufacturer and hospital actions in Figure 44. Here, $\omega$ is held constant. Similarly, in Figure 45, the contour of the hospital payoff is shown across the physician and hospital action dimensions, with constant values for the manufacturer’s decisions. When product value is low (Trial A), we see that $u_3$ is constant for most values of $\kappa$ in Figure 44. Here, as the hospital’s action reaches a restrictive level (at the lowest values of $\kappa$), then $u_3$ drops off to a low value. Likewise, when product value is high, restrictive actions on the hospital’s part decrease its payoff. This suggests that by implementing a restrictive cost control policy, the hospital may have a negative impact upon its own payoff.
Figure 44: Hospital’s Payoff for Selected Trials (Constant $\omega$)

Figure 45: Hospital’s Payoff for Selected Trials (Constant $\theta$ and $\rho$)
Further impact of the hospital’s price cap action upon player payoffs can be seen in Figures 46, 47, and 48. Here, the manufacturer and physician payoffs from Trial A are shown as a function of their actions ($\theta$, $\rho$, and $\omega$, respectively). In each figure, a line is shown for two cases – one in which the hospital is restricting the adoption, and another in which the physician’s adoption is not restricted. As evidenced here, the hospital’s cost control decision has the potential of affecting $u_1$, $u_2$, and $u_3$. In these examples, the hospital’s restrictive price cap ($\kappa = 0.05$) acts to limit the payoffs of all players. Similar results were also observed in Trial B.

Figure 46: Manufacturer’s Payoff Across $\theta$ (Constant $\rho$ and $\omega$)
The impact of the hospital’s cost control decision can be seen not only when looking at the payoff function behavior, but also when examining the Nash equilibria of these two trials more closely. Trial A resulted in
75 pure Nash equilibrium, and Trial B resulted in 39. Table 25 contains a summary of all equilibria. All Trial A equilibria are of a similar form: they occur at only one value for both $\theta$ and $\omega$, and for all values of $\rho$ that are greater than 3 months. However, the Trial B equilibria occur at two different values of $\theta$. The majority of the Trial B equilibria occur when $\theta = 72$ months; however several also occur at a more frequent update interval ($\theta = 24$ months).

In Trial B, none of the equilibria at the faster update pace receive a high Pareto ranking; in fact all players are worse off at these equilibria. This suggests that under some conditions, a coordination problem occurs in the three player PPI game, similar to the classic stag hunt game (discussed in Chapter 3). In all trials, we assumed a static game; in other words, players do not send signals to each other prior to making their decisions. If the hospital believes that the manufacturer will select a more frequent update, then its best response is to select a more restrictive ($\kappa = 0.8$) price cap strategy. Likewise, if the manufacturer believes that the hospital will select this more restrictive strategy, then its best response is to select a more frequent product update interval ($\theta = 24$ months). Despite this, everyone, including the physician (and, therefore, likely the patient), is better off with a less restrictive price cap and a longer time between new generation releases. Hospitals experiencing this type of coordination problem should then reach out to manufacturers to build relationships and collaborate to ensure all parties receive the best outcome.

Table 25: Trial A and B Equilibria

<table>
<thead>
<tr>
<th></th>
<th>$A_1$</th>
<th>$A_2$</th>
<th>$A_3$</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta$</td>
<td>$\rho$</td>
<td>$\omega$</td>
<td>$\kappa$</td>
<td></td>
</tr>
<tr>
<td>Trial A</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Low product value)</td>
<td>72 months</td>
<td>All 15 values where $\rho &gt; 3$</td>
<td>2 months</td>
<td>All 5 values where $\kappa &gt; 0.05$</td>
</tr>
<tr>
<td>Trial B</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(High product value)</td>
<td>72 months</td>
<td>All 16 values where $\rho &gt; 0$</td>
<td>1 month</td>
<td>Both values where $\kappa &gt; 0.8$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.8 price cap</td>
<td>7 NE, 0 top-ranked</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>24 months</td>
<td>All 7 values where $24 &gt; \rho &gt; 0$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

We also see from these two example trials that, given the set of equilibria for both trials, the average $\theta^*$ for Trial B (63.4 months, on average) is lower than that of Trial A (72 months). Therefore, under the limited conditions of these two trials, partial support was found for the hypothesized effects between adoption time, price caps, and the product value of the new PPI generation. In order to gain further insights into the impact of product value, all trials in the full factorial experiment were grouped into pairs, such that all factor levels for the trials in a given pair are equivalent except for the product value factor. Through this process, 1,380 pairs of trials were identified. In 11% of these pairs, a lower product update
interval was observed. Additionally, 36% of the pairs have a lower $\omega$. The trials that resulted in a lower average $\theta$ and a lower average $\omega$ are discussed further in Section 4.3.4.

Like Trials A and B discussed above, most trials in the Hospital Cost Control game experiment yielded at least one pure Nash equilibrium. Out of 2,976 trials, 264 resulted in no pure Nash equilibrium. As detailed in Section 3.2.2, this occurs when the payoff functions lead to a scenario in which each player’s strategy relies on “outrunning” the other player (Gibbons 1992). In the next sections, all trials which did result in one or more pure Nash equilibria are grouped into general classes of results with similar payoff outcomes. These payoff classes were further analyzed in order to provide insights into the role of the hospital within the PPI supply chain.

4.3.2 Understanding Expected Payoffs

To gain insights into the behavior of the three-player games, the Nash equilibria resulting from the 2,976 trials with one or more pure Nash equilibria were analyzed by applying the process described in Section 4.1. The payoffs associated with the top-ranked Nash equilibria for each trial were normalized across all Nash equilibria from the trials, leading to a range of 0% and 100%, for each player’s normalized payoff.

Prior to normalizing the payoffs, we see that the manufacturer and physician’s results have a range that similar to that observed in the Sales Rep experiment. However, the non-normalized range for the manufacturer (0.004 to 1.25 for top-ranked equilibria) extends to higher values than with previous games. This is not unexpected, as the addition of the claimed vs. actual value concept in the three-player formulation effectively allows for the manufacturer to receive a higher price per PPI than that modeled in earlier games. The non-normalized range for top-ranked physician payoffs in the three-player experiment (100.03 to 198.90) is also similar to the results in the Sales Rep Game. A wide range of non-normalized payoff values for the hospital was observed, ranging from -110.6 to 119.8. Because the hospital payoff is a mix of clinical results and cost, this quantitative value is unitless, and is used as an indicator representing the hospital’s success toward its goals. Negative hospital payoffs occurred under specific conditions, which are identified through the supervised learning algorithm (see Section 4.3.3). In order to apply this technique, the results were first classified into seven broad classes of similar results.

The boundaries defining each of the seven payoff classes were determined from visual inspection of the data, and are summarized in Table 26. The distribution of top-ranked equilibria across these payoff classes is summarized in Table 27. This distribution indicates that the hospital is able to achieve moderate to strong results in most all cases – only 14% of the Nash equilibria observed fall into payoff class 1. In this class, the other players also fare poorly, as compared to other trials. At the other extreme, all players achieve excellent results in payoff class 7. In the most frequently observed outcome, payoff class 4 (29%), the physician and manufacturer fare well, while the hospital’s payoff is only moderate.
Table 26: Payoff Class Ranges

<table>
<thead>
<tr>
<th>Payoff Class</th>
<th>Range for Normalized $u_1$</th>
<th>Range for Normalized $u_2$</th>
<th>Range for Normalized $u_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$0% \leq u_1 &lt; 40%$</td>
<td>$0% \leq u_2 &lt; 15%$</td>
<td>$0% \leq u_3 &lt; 25%$</td>
</tr>
<tr>
<td>2</td>
<td>$0% \leq u_1 &lt; 40%$</td>
<td>$0% \leq u_2 &lt; 15%$</td>
<td>$25% \leq u_3 &lt; 41%$</td>
</tr>
<tr>
<td>3</td>
<td>$0% \leq u_1 &lt; 90%$</td>
<td>$15% \leq u_2 &lt; 80%$</td>
<td>$25% \leq u_3 &lt; 41%$</td>
</tr>
<tr>
<td>4</td>
<td>$50% \leq u_1 &lt; 100%$</td>
<td>$80% \leq u_2 &lt; 100%$</td>
<td>$25% \leq u_3 &lt; 41%$</td>
</tr>
<tr>
<td>5</td>
<td>$0% \leq u_1 &lt; 40%$</td>
<td>$0% \leq u_2 &lt; 15%$</td>
<td>$41% \leq u_3 &lt; 100%$</td>
</tr>
<tr>
<td>6</td>
<td>$0% \leq u_1 &lt; 90%$</td>
<td>$15% \leq u_2 &lt; 80%$</td>
<td>$41% \leq u_3 &lt; 100%$</td>
</tr>
<tr>
<td>7</td>
<td>$50% \leq u_1 &lt; 100%$</td>
<td>$80% \leq u_2 &lt; 100%$</td>
<td>$41% \leq u_3 &lt; 100%$</td>
</tr>
</tbody>
</table>

Table 27: Frequency of Payoff Classes

<table>
<thead>
<tr>
<th>Payoff Class</th>
<th>Distribution of Top-Ranked Equilibria</th>
<th>Degree of Payoff</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Manufacturer</td>
<td>Physician</td>
</tr>
<tr>
<td>1</td>
<td>14%</td>
<td>Poor</td>
</tr>
<tr>
<td>2</td>
<td>23%</td>
<td>Poor</td>
</tr>
<tr>
<td>3</td>
<td>6%</td>
<td>Poor to Moderate</td>
</tr>
<tr>
<td>4</td>
<td>29%</td>
<td>Moderate to Excellent</td>
</tr>
<tr>
<td>5</td>
<td>10%</td>
<td>Poor</td>
</tr>
<tr>
<td>6</td>
<td>4%</td>
<td>Poor to Moderate</td>
</tr>
<tr>
<td>7</td>
<td>14%</td>
<td>Moderate to Excellent</td>
</tr>
</tbody>
</table>

By plotting the payoffs for each Nash equilibrium across three dimensions, groupings of the seven payoff classes can be observed. These results, represented as a projection into two planes $(u_1-u_3)$ and $(u_2-u_3)$, are shown in Figures 49 and 50, respectively. The distribution of the top-ranked equilibria across the $u_1-u_2$ plane was quite similar to the previous two-player games, and is therefore omitted here. In both figures, the payoff classes discussed above are shown. Especially in the $u_2-u_3$ plane, a clear distinction between the classes can be observed. However, in Figure 49, some overlap between the payoff classes is apparent across the manufacturer payoff dimension ($u_1$). This suggests that the manufacturer’s results have less connection to the hospital results than those of the physician.

These figures also suggest that the hospitals results are, at times, correlated with the results of the other players. When considering only Payoff Classes 5, 6, and 7, a positive correlation between the results for the hospital - manufacturer, and the hospital - physician, is observed. This indicates that, unlike the two-player game, some trials represented scenarios in which the hospital is at odds with the other players. However, in other trials, the hospital’s results are strongly tied to the results of the manufacturer and physician. For these particular situations, a natural incentive may exist for the hospital and manufacturer to develop a relationship. In all others, it is likely that the hospital would benefit by proactively working towards coordination with the manufacturer and physician.
Figure 49: Manufacturer vs. Hospital Results with Payoff Classes

Figure 50: Physician vs. Hospital Results with Payoff Classes
Following the classification-by-inspection into seven payoff classes, the distinguishing characteristics of the trials were identified using the supervised learning algorithm. These results are presented in Section 4.3.3.

4.3.3 Differentiating between Payoff Classes

As with earlier games, the Hospital Cost Control experiment results were analyzed with the method described in Section 4.1. The decision tree resulting from the application of the C4.5 supervised learning algorithm is in Figure 51. Additional details from the supervised learning calculations can be found in Appendix D.

This decision tree indicates that the hospital emphasis on cost versus clinical results has a strong impact upon the game outcome. For ease of discussion, we classify a hospital as a *research hospital* when cutting edge clinical improvements are valued over cost savings ($\alpha = 75\%$), and as a *non-research hospital* when the hospital values cost savings and is satisfied with the current clinical results ($\alpha = 25\%$). For a non-research hospital, the players can expect to find themselves in one of many payoff classes, depending upon other characteristics of their supply chain. In these cases, supply chain characteristics impact the magnitude of the payoffs, such as the physician’s loyalty to the manufacturer, the manufacturer’s tendency to overestimate product value, and the maximum product value of the new generation, and the associated speed to market. Most prominently, the physician’s willingness or ability to divert procedures to another facility plays a role in distinguishing the outcome in these trials.

If the physician is unlikely to divert procedures to another facility, then everyone’s payoffs are low. However, if it is likely for the physician to divert procedures to a facility that allows for the adoption of the new PPI generation, then the payoff results for all players improve. At first glance, this may seem counter-intuitive. However, it can be explained by considering a few aspects of the game. First, in these cases, the physician has a low likelihood of switching manufacturers. Additionally, the hospital has placed its focus upon cost savings over cutting-edge clinical results, and the manufacturer has overestimated the new generation’s value – thus increasing the unit cost to the hospital, and revenue for itself. Because of this, the opportunity cost that is “lost” when the physician diverts patient volume is actually a gain for the hospital, because of the negative impact that each of these cases would have upon the hospital’s cost savings goals. Due to the physician's ability to leverage his privileges with another medical institution, he is able to adopt the new generation and benefit from its improved clinical value. Finally, because the physician will adopt the new generation for many of his procedures, and the revenue received by the manufacturer for each unit is high, the manufacturer also has outstanding results. This
result implies that all members of the PPI supply chain benefit when a physician has an affiliation with an additional hospital that places more emphasis on cutting edge technology than cost.

For supply chains involving non-research hospitals, it may be mutually beneficial for all players that the physician treat some patients at another facility that allows for the adoption of the new product generation. Hospitals considering this strategy may benefit by further research that addresses the volume-cost savings tradeoff that is at play for a particular PPI.

In contrast to this, for supply chains involving research hospitals ($\alpha = 75\%$), the players can expect results in payoff class 5, 6, or 7. The hospital payoff is positively correlated with those of the manufacturer and physician. Even if the incremental product value is low for successive generations, the
hospital payoffs were significantly stronger as compared to trials where $\alpha = 25\%$ or $50\%$. Not surprisingly, this finding indicates that hospitals which emphasize clinical advancements over cost control will have incentives somewhat aligned with the manufacturer and physician. As the emphasis on clinical advancements increases, the three players are likely to be competing less and may find that a natural synergy exists in these scenarios.

Finally, if the hospital places equal value upon both clinical results and cost savings, essentially no correlation is observed between the hospital’s results and those of the manufacturer and physician. While both the research and the non-research hospital were observed to achieve the ideal payoff class (Payoff Class 7), the equal-valuation hospital ($\alpha = 50\%$) did not. Despite the presence of multiple payoff classes (2, 3, and 4), the hospital’s payoffs were moderate in all three classes, relative to the results for the research and non-research hospitals. This result indicates that trying to provide the newest innovations while minimizing cost is a poor policy for the hospital. With this dual focus, the hospital can never reach the ideal class (Payoff Class 7). Instead, the hospital is better off developing a clear vision for each specialty (or procedure) for which PPI play a significant role. The hospital should decide if the objective is to provide cutting-edge, innovative services, or to provide quality, mainstream care in the most affordable manner.

If the hospital does not make this decision, and both innovation and cost are equally valued, the manufacturer and physician results vary. When cost and clinical results are equally weighted by the hospital and incremental product value provided by the new PPI generation is low, then the manufacturer and physician cannot expect to see large payoffs. If incremental product value is high and the physician is unlikely to divert patients to another facility, then as long as the manufacturer underestimates the new product value, the manufacturer and physician generally have strong results. However, if the manufacturer does not underestimate the new product value, then the results for both are comparable to the case when the new product value is low.

In the cases with high incremental product value and accurate or over-estimation of the product value from the manufacturer, a physician’s willingness to switch to another facility can, at times, play a significant role in the players’ outcomes. Because of the impact this can have upon distinguishing the game’s outcome, the hospital which values cost control and cutting edge clinical results equally would benefit by understanding the tendencies of its physician population. To that end, it may be useful for the hospital to perform physician surveys, or build other channels of communication with physicians in order to understand under what conditions they would utilize privileges at another institution. In light of the results from the three-player experiment, future research that investigates physician decision-making regarding facility selection may be of benefit – especially to hospitals that equally value cost control and improved clinical outcomes.
Under the equally weighted hospital valuation scenario ($\alpha = 50\%$), if the physician is unlikely (or unable) to divert patients to a different facility in order to adopt the new PPI generation, and the clinical value achievable with the new generation is high, results suggest that PPI pricing begins to impact the manufacturer and physician payoffs. If the manufacturer underestimates the product value, the manufacturer and physician will have significantly better results. In other words, if the average hospital purchasing the PPI values cost control and clinical improvements equally, the manufacturer and the physician may also stand to benefit if the profit margin per unit is reduced as much as possible. While this result is somewhat counterintuitive for the manufacturer, it suggests that the price-volume tradeoff typical in many industries can begin to play a key role for the PPI supply chain under these conditions. This finding emphasizes that in certain scenarios, or for certain hospitals, the manufacturer’s pricing decision begins to play a more important role. Because the manufacturers’ pricing decision was not explicitly modeled here, future research on the PPI manufacturer’s pricing behavior is warranted. It may also be interesting to consider in future work how the manufacturer may best tailor its PPI prices based upon hospital willingness to pay. In order to successfully achieve this, research on forecasting hospital willingness to pay would be of value to the manufacturer.

Regardless of the hospital’s emphasis on cost control vs. improving clinical results, our results suggest that adding the hospital into the game in an active role can lead to a wide range of outcomes – most notably for the hospital itself. The outcome is highly dependent upon a variety of supply chain characteristics, which may be different for each supply chain. Because the hospital may be procuring dozens, if not hundreds, of types of PPI for different specialties, it is worthwhile to note that the hospital should not take a one-size fits all approach when selecting its PPI cost-control policies.

4.3.4 Exploring the Effects of Incremental Product Value

In Section 4.3.1, it was observed that grouping experimental trials together into pairs, such that each pair had all parameters equivalent except the expected clinical value of the new PPI generation, indicated partial support for the hypothesis that with only a small clinical improvement over the current product version and hospital restrictions on physician adoption, $\theta$ and $\omega$ at equilibria both increase. Given these pairs, 11% and 36% of pairs had lower average $\theta$ and average $\omega$, respectively, when the incremental clinical value was low for the new generation. For fifty pairs of trials, both of these cases hold true. These fifty pairs (100 trials) provide support for the hypothesis, therefore, we investigated this subset more closely.

First, to understand when the supporting cases occurred, the C4.5 classification algorithm was applied to all trials to predict which experimental factors lead to a trial’s membership in the group of 50 pairs. As
shown in the resulting decision tree, Figure 52, these pairs were found to occur for the research hospital, only when the patient volume was low, peer learning was high, and the manufacturer accurately estimated the clinical value of the new generation. Additionally, the effectiveness of the manufacturer’s R&D efforts over time was observed to play a role.

Second, to understand the outcomes of these trials, the C4.5 method was applied to the subset of 100 trials (50 pairs) to predict the payoff classes within this subset of trials. The resulting decision tree is in Figure 53. Within this subset of trials, the Nash equilibria results were observed in Payoff Classes 5, 6, and 7. These payoff classes represent the highest payoff classes for the hospital, and within this set, payoff class 7 is the highest payoff class for all players. From the supervised learning results, it is clear that for PPI procedures with low volume occurring at a research hospital with strong peer learning, the following are key factors that distinguish between mediocre and outstanding player results:

- clinical value,
- physician loyalty to the manufacturer, and
- manufacturer’s pricing.
4.3.5 Actions at Equilibria

To investigate the relationship between the optimal actions and resulting payoff classes, we analyzed the relationship between the Nash equilibria actions and payoffs. This analysis was performed by applying the procedure described in Section 4.1 to all trials in the full-factorial experiment that resulted in one or more pure strategy Nash equilibria. As before, the players' action spaces were segmented into a partition across the players' action space (see Table 18). Then, the observed segments were categorized into action groups. The action groups were subsequently mapped to the payoff classes in order to identify how the different types of player decisions correlate to the expected player payoffs. Substantially more variation in the actions at equilibria was observed in the three-player experiment, as compared to earlier two-player experiments. This is expected, as the introduction of the third player expands the set of actions by a factor of five.

No specific results or patterns emerged from the analysis of action groups for the three-player game. Despite this, it was observed that some trials resulted in multiple equilibria where the manufacturer and physician actions and payoffs were identical across all tied equilibria, but one of the tied equilibrium occurred at each value of the hospital price cap decision. These occurrences imply that, in some cases,
the hospital’s price cap strategy will have no impact upon the physician and manufacturer’s actions. All of these trials occurred when the hospital values clinical advancements as much, or more, than cost control – i.e., research hospitals. This highlights that the cost control action may not be a relevant approach for research hospitals to consider at all. As the hospital places more and more emphasis on clinical value over costs, a cooperative game or signaling game may be a better fit for these supply chains, because it is in these hospitals’ best interest to enable – not prevent – the adoption of a truly improved product.

To further understand the effects of the hospital’s emphasis on cost control on the game outcome, Figure 54 plots $\mu_3$ and its associated emphasis on clinical results over cost. The size of each bubble indicates the frequency at which the combination occurs. Since the restrictiveness of $\kappa$ is relative to the claimed product value, the scenarios described in Section 3.3.3.3 are used here to indicate the players’ actions at each equilibria. Only three of the four scenarios were observed in the top-ranked equilibria of the full-factorial experiment: Scenario B, where the hospital does not restrict adoption and the physician does adopt; Scenario C, where the hospital restricts adoption and the physician does not adopt; and Scenario D, where the hospital restricts adoption and the physician does want to adopt. These scenarios are used to summarize optimal actions in Figure 54.
For the non-research hospital ($\alpha = 0.25$), when it is optimal to restrict the adoption of the new generation they are able to move from payoff class 1 into payoff classes with higher results for themselves, and also other players (payoff classes 7, 8, and 9). However, for the research hospital ($\alpha = 0.75$), a restrictive payoff cap is almost never optimal. Clearly, the benefit of restricting a physician’s adoption is highly dependent upon the hospital’s goals. These results indicate that the hospital administration should develop well-defined goals for their organization, and articulate how each specialization (and its associated PPI) supports those goals. With this vision clearly laid out, personnel involved with PPI procurement can work to either develop effective price caps (cost control focus), or reach out to PPI manufacturers to garner the latest-and-greatest technology that will support their strategy (clinical improvement emphasis).
5. Conclusions

5.1 Manufacturer-Physician Game Conclusions

The results of the manufacturer-physician PPI update model support the hypothesis that the average physician’s ability to master a new generation of PPI impacts the timing of his adoption of the new product, which decreases the frequency of the manufacturer’s ideal $\theta$. Not only is $\theta$ dependent upon learning, there is benefit to both the manufacturer and the physician when a PPI requires a shorter amount of time to be mastered. Results also suggest that manufacturers may have much to gain by investing in product development activities that have low complexity because a new PPI generation with this quality will enable the physician to master it more quickly. In an industry that is heavily involved in research and development activities, this insight can assist manufacturers who are vying for physicians when their competitors are frequently producing new product generations with high complexity and little added-value.

Additionally, results demonstrate the importance of a product’s clinical value. We see that the benefits of introducing a new PPI generation, for both the manufacturers and the physicians, are highly sensitive to the new generation’s actual clinical value. The results show that the physician is better off not adopting a new PPI product update if it has little additional clinical value and a significant learning curve. It is also clear that if the market for a given PPI that has a high frequency of product updates with relatively little real clinical value, a manufacturer will benefit with less frequent and more valuable product updates. If a given PPI market is flooded with low value product updates, policy-makers may consider more stringent regulations for new product approvals, in order to ensure that new products meet some threshold of additional clinical value. This may reduce the frequency of new product generations for physicians to learn and focus research dollars upon more pivotal developments. Manufacturers, physicians, and even patients, can benefit from the addition of high-value features to PPIs.

Finally, the results presented in Section 4.2 demonstrate that the PPI manufacturer’s outcome is positively correlated with the physician’s outcome. If the physician experiences an improvement in clinical results due to the adoption of a new PPI product generation, the manufacturer will benefit, as well. This suggests that there is much to gain, for both the manufacturer and the physician, by entering into partnerships to develop PPIs with high clinical value and low complexity. Policy-makers should be aware of this mutual benefit to ensure that regulations protect other members of the PPI supply chain from any potentially harmful effects of manufacturer-physician partnerships, while also protecting and encouraging appropriate collaborations that allow true innovations to flourish. If a new PPI generation has high value because it improves outcomes for the patients that ultimately receive it, then it is also in the patients’ best interest for the manufacturers and physicians to cooperate where possible to develop new generations of PPIs.
5.2 Sales Rep Game Conclusions

Because the Sales Rep Game was based upon modified versions of the original payoffs for the manufacturer and physician, it is not surprising that its findings support the conclusions drawn from the original model. The importance of market characteristics, such as customer loyalty and achievable product value, again surfaced in the findings presented in Section 4.3. Results discussed in this section also support the hypothesis that by providing a sales rep to train and assist the physician, the manufacturer benefits with an increased frequency of new PPI generation releases.

First, we see that some trials from the Sales Rep Game full-factorial experiment provided examples in which the PPI manufacturer has an incentive to select the fastest product update pace possible. Despite this motivation, the optimal strategy for the manufacturer is to select a somewhat slower update pace for the physician’s benefit even in these cases.

When the product value that the manufacturer could achieve with a long development cycle was low, experimental results indicated that quicker product update paces were optimal if the manufacturer was able to capture the majority of the new generation’s product value earlier in the development cycle. When the achievable product value was high, quicker product update paces were optimal also if the majority of the product value could be captured early on, and additionally if the physicians had a high likelihood of switching manufacturers over time. Although the manufacturer’s optimal product update pace was more frequent in these instances, results suggest that both the manufacturer and the physician will find their payoffs to be significantly improved if it is feasible for the manufacturer to delay the release of a new PPI generation in order to gain significant product value. Despite this result, it is worth noting that both the physician and the manufacturer reached strong payoff results (Payoff Class 4) when the physician’s probability of switching manufacturers was high in the long run. For this to occur, physician loyalty must decay slowly at first, while the manufacturer strives to incorporate the most product value possible in a shorter period of time.

Aside from product value, the Sales Rep Game experiment indicates that an increase in the sales rep’s ability to provide effective training to the physician also had a positive effect upon the physician payoffs. This work modeled an improvement in the physician’s clinical results with a sales rep that is effective at providing training. Results indicate that within a given scenario, the physician is almost always better off with a sales rep that provides effective training over one that does not. Based upon this finding, the physician’s best strategy is to select a PPI that is produced by a manufacturer that provides not only excellent product value, but also high quality training.

Additionally, the Sales Rep experiment reinforced the importance of the physician’s loyalty to the manufacturer. Interestingly, the likelihood of switching manufacturers has a significant impact on not only
the manufacturer’s results, but the physician’s outcome as well. This is primarily due to the slower product update paces that become optimal for the manufacturer if the physician’s likelihood of switching is reduced or postponed. When the threat of losing customers is reduced, the pressure upon the manufacturer to release a new product generation is alleviated, and the manufacturer can release new PPI generations with a higher product value at a slower pace. Therefore, the manufacturer should strive to create a sales force that will defer or discourage physicians’ brand switching decisions. If the manufacturer must earn and sustain physician loyalty by providing high incremental product value and effective training, then they will have an incentive to provide both. Although training provided by sales reps can act to reduce the optimal time between product updates, its effects upon physician loyalty may be of more significance to both parties.

5.3 Hospital Cost Control Game Conclusions

With the hospital included in the PPI supply chain game, the strong correlation between manufacturer and physician was consistent with previous results. It was originally hypothesized that price cap restrictions by the hospital would lengthen the time between product updates and delay physician adoption. The experiment results provided partial support for this hypothesis, occurring in trials representing scenarios at a research hospital when the patient volume is low, peer learning is high, and the manufacturer accurately estimates the clinical value of the new generation.

For a research hospital, which values clinical improvements over cost control, implementing a price cap to restrict physician adoption of new PPI generation could harm its own objectives. In these cases, the PPI supply chain has similarities with the classic stag hunt game, in which everyone is better off only if the players coordinate. The hospital may benefit by reaching out to the PPI manufacturer, or perhaps the physician, in order to provide itself with prior knowledge of the manufacturer’s new product generation release strategy. In these cases, all players have similar incentives, and are likely not at odds with each other. Because of this, further research that models the PPI supply chain as a signaling or cooperative game may be insightful.

However, for cost-conscious non-research hospitals that find the level of clinical results provided by the current PPI generation to be satisfactory, all players may benefit if the physician has another hospital that supports adoption. In these cases, it is important that the hospital has a good understanding of the volume loss-cost savings tradeoff that would occur as the physician diverts patients to another facility. This result is somewhat reliant on our assumption that the expected clinical improvement of the product is the actual clinical improvement. If there is uncertainty in the validity of the new generation’s advancements, then future research may be beneficial to understand how this uncertainty impacts the game.
When the new PPI generation is expected to have a high incremental clinical value and the manufacturer provides an accurate or slightly inflated price, the physician’s willingness to perform procedures at another hospital can distinguish between lower and higher manufacturer and physician results. If the hospital has not decided to be either cost- or innovation-centric and values clinical improvements and cost control equally, then the hospital should conduct physician surveys or other forms of communication with the physician to develop an understanding of when its physicians would choose to practice at another institution. Because our results indicate that the physician’s willingness-to-divert can, at times, distinguish between the game outcomes, future empirical research on the physician facility selection behavior may be beneficial.

Also in the case of a dual-focused hospital, the manufacturer and the physician may benefit if the manufacturer’s price for the hospital is reduced as much as possible. By doing so, the manufacturer increases the attractiveness of the new generation to the hospital. Because the manufacturer’s pricing strategy was not directly modeled here, further research in this area may be of benefit. For example, if the manufacturer is able to negotiate prices directly with the hospital, or with a group of hospitals with similar cost and clinical improvement objectives, then work on price optimization that leverages willingness to pay may be helpful for the PPI manufacturer. Additionally, if the hospital happens to be a key client with influence over other hospitals or major consumer of the manufacturer’s PPI, it may have a stronger influence on the members of the supply chain. This possibility was not incorporated into the formulation of this work, and this could be addressed in a modified formulation of the three-player game.

5.4 Limitations and Future Work

The findings in this work are driven by the form of the payoff functions, and their components, such as rate of diffusion of a new PPI generation throughout the physician population, the relationship between the new product generation’s value and the manufacturer’s selected product update interval, and the impact of the manufacturer’s product update interval and rollover policy upon physician adoption decisions. While this work considers several scenarios for each of these relationships, the results may be enhanced by empirical studies which focus on each of these relationships. For example, future work could focus on data collection to capture how the product update pace and product discontinuation decisions affect the physician’s loyalty to their preferred manufacturer. For these results to provide insights directly to a manufacturer or physician regarding a specific PPI (e.g. a knee implant or a pacemaker), empirical evidence is required to identify the characteristics of the supply chain for the specified PPI.

In addition to empirical studies which investigate the supply chain characteristics that were used here as model inputs, an empirical study which addresses the differences and similarities between PPI supply
chains for different types of PPIs would be beneficial. Because the product characteristics for PPIs vary widely across different physician specialties, an empirical investigation to compare the update and adoption decisions across fields such as orthopedics, cardiology, and neurology, would provide insights into how the manufacturers and physicians within each of these fields interact differently. It also might indicate how different product features and characteristics affect the update pace, rollover policy, and adoption decisions.

The findings from the manufacturer-physician game indicate that a PPI should be both easy to learn, as well as have high clinical value, in order to benefit both the manufacturer and physician. It would be pertinent for future work to analyze this tradeoff of R&D resources more closely. Finally, the results regarding the PPI product update, rollover policy, and adoption decisions were derived from a non-cooperative game framework. Our results demonstrate that both the manufacturer and the physician have mutual interests. Therefore, future analysis using a cooperative game approach is warranted. Also, this work assumed that the players have no prior knowledge of the others’ actions. It could be argued that once a manufacturer establishes and maintains an update pace, the hospital and physician will have this information when making their future adoption and cost control decisions. A leader-follower game may be appropriate to model this additional complexity in the future. Additionally, in these games, all players were assumed to have similar influence in the games. Future research addressing the possibility of unequal influences from the players may be investigated via a principal-agent approach.

Within the Sales Rep formulation, sales rep effectiveness was primarily represented by two factors: the shape of the probability of switching curve, and the sales rep gain factor which reduced the time required by the average physician to master the new PPI generation. However, these factors were modeled independently; in this work, the sales rep’s training effectiveness had no impact upon the physician’s probability of switching function. Although a direct relationship between sales rep training effectiveness and physician loyalty was not modeled, a variety of factors representing the magnitude and behavior (shape/form) of the physician population’s loyalty was incorporated into the full-factorial experiment for the Sales Rep Game. Clearly, the likelihood that the physician will remain loyal to the manufacturer is a characteristic which distinguishes between marginal and outstanding outcomes for the manufacturer, and not surprisingly, the physician. Because we find that the sales rep’s training effectiveness is of clear benefit to the physician, and physician loyalty plays such an important role upon both players’ outcomes, future empirical studies that investigate the impact of training from sales reps upon physician loyalty could provide worthwhile insights for PPI manufacturers that utilize sales representatives.

In this study, product value continually surfaced as a key factor that determines player payoffs. This result emphasizes the crucial role that the physician plays in screening new generations of PPI available in the marketplace. Clearly, product value is the most significant driver of both the manufacturer and the
physician payoffs. In this work, we assume that the product value perceived by both players is the true product value. However, if the manufacturer exaggerates the product value and the physician is unsuspecting of this strategy, then the physician will realize an outcome that is less than that predicted by the game. This work did not directly address hidden information and signaling, but further investigation of this type of behavior, as it relates to product value, would be of benefit.

Additionally, this work tested how a variety of scenarios might impact the payoffs for each player. Another area of future work which has potential is to perform empirical studies to determine the correspondence between a PPI supply chain and different scenarios. For example, in the pacemaker supply chain, physicians may have a negligible probability of switching brand preferences, and the manufacturer may be able to incorporate significant product value quickly by incorporating new software features into its product. However, it is quite possible that a manufacturer for a different type of PPI, like an artificial hip, may experience less physician loyalty and slower development of value-added features such as enhanced material or mechanical properties. In order to further connect the findings from this work to the supply chains for specific devices, it will be important in the future to understand which scenarios tested here apply to the supply chains for specific products.
Appendix A: Glossary

**Action group**
Cluster of similar player actions at equilibria

**Adoption time**
Number of months after new generation release that physician adopts; physician decision

**Arthroplasty**
Surgical joint replacement procedure

**C4.5 algorithm**
Algorithm for generating decision tree

**Clockspeed**
Term referring to the speed of innovations, new product releases, and changes within an industry

**Gainsharing**
Strategy used by hospitals and other service providers to share cost and efficiency gains with physicians as financial bonuses or other perks

**Game theory**
Modeling technique to represent interactions between multiple decision makers in a given scenario ("game")

**k-folds cross validation**
Data hold-out strategy for testing predictive model; random sample of observations held out from data used to generate model and compared against model results and repeated "k" times

**Nash equilibrium**
Outcome(s) of game occurring when each player selects a strategy that will maximize his playoff, considering that other players will take actions to maximize their own payoffs

**Pareto ranking**
Algorithm which ranks equilibria from most ideal outcome to least ideal outcome

**Payoff class**
Classification of similar player payoff results at equilibria

**Physician preference item**
One-time use supply used for healthcare services that is selected by physician based upon personal preferences and/or clinical opinions and paid for by hospital

**Product update interval**
Number of months between product generation releases; manufacturer decision

**Product rollover policy**
Number of months for product generation to remain on market after introduction of new generation; manufacturer decision

**Supervised learning**
Data mining techniques which seek to predict the value of a target variable
Appendix B: Acronyms

CBO: Congressional Budget Office
CRM: Customer Relationship Management
FDA: Food and Drug Administration
GPO: Group Purchasing Organization
PPI: Physician Preference Item
R&D: Research and Development
Appendix C: Mathematical Derivations

Expressing $\lambda_2$

1. From (6), define the minimum value of $\lambda_2$ to be $\left(\frac{\omega_{\text{max}} + 1 - \omega_{\text{min}} - 1}{\omega - \omega_{\text{min}} - 1} - 1\right) \lambda_1$ when the product rollover policy is sufficiently large enough to not influence the physician adoption time ($\rho_2 \leq \rho$).

2. Define the maximum value of $\lambda_2$ to be $k$ percent ($k > 1$) of the minimum value of $\lambda_2$, when the product rollover policy reaches its maximum level of influence ($\rho \leq \rho_1$):

\[
\lambda_2 = \left(\frac{\omega_{\text{max}} + 1 - \omega_{\text{min}} - 1}{\omega - \omega_{\text{min}} - 1} - 1\right) k \lambda_1
\]

3. Assume $\lambda_2$ is a linear function of $\rho$ when $\rho_1 < \rho < \rho_2$:

\[
\lambda_2 = m \rho + \delta
\]

4. Given two points, $\left(\rho_1', \left(\frac{\omega_{\text{max}} + 1 - \omega_{\text{min}} - 1}{\omega - \omega_{\text{min}} - 1} - 1\right) \lambda_1 \right)$ and $\left(\rho_2', \left(\frac{\omega_{\text{max}} + 1 - \omega_{\text{min}} - 1}{\omega - \omega_{\text{min}} - 1} - 1\right) \lambda_1 \right)$, the slope ($m$) and intercept ($\delta$) can be calculated. Using the definition of slope ("rise over run") leads to:

\[
m = \frac{\left(\frac{\omega_{\text{max}} + 1 - \omega_{\text{min}} - 1}{\omega - \omega_{\text{min}} - 1} - 1\right) \lambda_1}{\rho_1 - \rho_2}
\]

Substituting this slope and a single given point into the definition of a line yields the intercept:

\[
\delta = \left(\frac{\omega_{\text{max}} + 1 - \omega_{\text{min}} - 1}{\omega - \omega_{\text{min}} - 1} - 1\right) k \lambda_1
\]

5. Inserting the slope and intercept back into the definition of a line gives the following expression, which represents $\lambda_2$ when $\rho_1 < \rho < \rho_2$:

\[
\lambda_2 = \left(k \lambda_1 - \left(\frac{\omega_{\text{max}} + 1 - \omega_{\text{min}} - 1}{\omega - \omega_{\text{min}} - 1} - 1\right) \lambda_1 \right) (\rho - \rho_1) + \left(\frac{\omega_{\text{max}} + 1 - \omega_{\text{min}} - 1}{\omega - \omega_{\text{min}} - 1} - 1\right) k \lambda_1
\]

Expressing $R(t)$ and $b$

1. The physician’s initial clinical results are given as $R(0)$.

2. The physician’s maximum clinical results given the new product generation’s value (upon completion of the learning curve) are given as $(1 + V(\theta))R(0)$. 
3. To derive the learning curve segment of the piecewise function, first the power function \((Y = cx^b)\) must be shifted according to the selected adoption time, \(\omega\):
\[
x = t - \omega t = \omega
\]
Then, it must be shifted again to allow for a clinical results value at the first procedure \((t = \omega)\) to be greater than zero. This shift \((Z)\) is calculated by setting the function equal to the expected clinical results at the first use and solving for the value of the shift. The expected clinical results at the first use is defined to be \(DR(0)\), and the expected clinical results at the first use when \(t = 0\) \((c)\) is defined to be \(D(0)R(0)\). Therefore,
\[
D(\omega)R(0) = D(0)R(0)(t - \omega + Z)^b
\]
Solving for \(Z\) when \(t = \omega\) gives:
\[
Z = \left(\frac{D(\omega)}{D(0)}\right)^{1/b}
\]
This leads to the expression
\[
D(0)R(0)\left(t - \omega + \left(\frac{D(\omega)}{D(0)}\right)^{1/b}\right)^b
\]
4. Finally, the learning curve slope, \(b\), must be expressed in terms of the model parameters. Given that it will take \(L\) procedures for the average physician to progress from the initial clinical results, \(D(0)R(0)\), to the maximum clinical results possible, \((1 + V)R(0)\), and that the average physician expects to perform \(P\) procedures each month, then the entire learning process can be completed in \(L/P\) months. This leads to:
\[
(1 + V(\theta))R(0) = D(0)R(0)\left(\frac{L}{P}\right)^b
\]
Solving this expression for \(b\) yields:
\[
b = \frac{\ln \frac{1 + V(\theta)}{D(0)}}{\ln \frac{L}{P}}
\]
5. Combining each of these components leads to the piecewise function for \(R(t)\) shown below:
To define the points in time at which the piecewise function, $R(t)$, changes segments, it is necessary to find an expression for the point in time at which the maximum value of the clinical results is first reached by completing the learning curve. First, the expression for the learning curve is set equivalent to the maximum possible clinical value, $(1 + V)R(0)$:

$$(1 + V(\theta))R(0) = D(0)R(0) \left( t - \omega + \frac{D(\omega)}{D(0)} \right)^{1/b}$$

Then, solving for $t$ results in:

$$t = \left( \frac{1 + V(\theta)}{D(0)} \right)^{1/b} - \left( \frac{D(\omega)}{D(0)} \right)^{1/b}$$

When $b \neq -1$, the resulting integration is equivalent to:

$$u_2 = \frac{1}{t_3} \left[ R(0)(t_1 - 0) + D(0) \cdot R(0) \frac{ \left( t - \omega + \frac{D(\omega)}{D(0)} \right)^{b+1} }{b+1} \right]_{t_1}^{t_2} + (1 + V(\theta)) \cdot R(0) \cdot (t_3 - t_2)$$

Incorporating the Sales Rep Gain Factor into the Physician Payoff Function

1. The initial drop in clinical results when the physician adopts at time zero, is reduced by $\alpha$ percent. To accomplish this, we define the magnitude of the original drop ($X$) and the magnitude of the modified drop ($X'$).

$$X = R(0) - R(0)D(0)$$

$$X' = R(0) - R(0)D'(0)$$
2. Then we define \( X' = (1 - a)X \) to ensure that the sales rep-adjusted drop is \( a \) percent smaller than the magnitude of the drop from the original model. Solving this set of equations leads to

\[
D'(0) = a + (1 - a)D(0)
\]

3. Following the result from step 2, several parameters in steps 1-8 above are replaced by modified versions for the Sales Rep model.

- Parameter \( D(0) \) is replaced by \( D'(0) \)
- Parameter \( D(\omega) \) is replaced by \( D'(\omega) \)
- Parameter \( L \) is replaced by \( L' \)
- Parameter \( b \) is replaced by \( b' \)
- Parameter \( t_2 \) is replaced by \( t_2' \)
Appendix D: Confusion Matrices

Table 28: Game I Payoff Class Confusion Matrix

<table>
<thead>
<tr>
<th>Class</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
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<tbody>
<tr>
<td>1</td>
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<td>0</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>241</td>
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</tbody>
</table>

Table 29: Game II Payoff Class Confusion Matrix

<table>
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<th>3</th>
<th>4</th>
<th>5</th>
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<td>0</td>
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<tr>
<td>4</td>
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<td>0</td>
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<tr>
<td>5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>504</td>
</tr>
</tbody>
</table>

Table 30: Game III Payoff Class Confusion Matrix

<table>
<thead>
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<th>Class</th>
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<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
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<td>3</td>
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<td>0</td>
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<td>0</td>
<td>0</td>
<td>4536</td>
</tr>
</tbody>
</table>
Appendix E: Matlab Code

Game I Matlab Code

Figure 55: Game I Code Flow

Game I full_factorial_trials.m

%SET FIXED INPUTS
max_horizon = 48;
tauhat_1 = 0;
tauhat_2 = max_horizon+1;
R_0 = 100;
V_0 = 0;
fixed = [max_horizon; tauhat_1; tauhat_2; R_0; V_0];

%DEFINE FULL FACTORIAL EXPERIMENT
%Define ranges for factors
rhohat_1_vector = [9,24];
rhohat1_2delta_vector = [9,24];
k_vector = [1.1, 4];
lambda_1_vector = [1.1, 4];
Vhatdelta_vector = [.1, 1];
D_0_vector = [.1, .75];
q_vector = [.005, .1];
L_vector = [15, 100];
P_vector = [1, 10];
bathtub_vector = [1,2,3];

bathtub_1 = [1;0.16;
0.1;0.07;0.04;0.03;0.025;0.02;0.015;0.013;0.01;0.009;0.008;0.008;0.009;0.01;0.013;0.015;0.02;0.025;0.03;0.04;0.07;0.1;0.16]; %original
bathtub_2 = [2;
0.6;0.42;0.3;0.2;0.12;0.05;0.025;0.02;0.008;0.008;0.008;0.008;0.008;0.009;0.01;
0.1;0.013;0.015;0.02;0.025;0.03;0.04;0.07;0.1;0.16]; %trails off
bathtub_3 = [3;
0.16;0.13;0.07;0.04;0.03;0.025;0.02;0.015;0.013;0.01;0.009;0.008;0.02;0.025;0.05;0.12;0.2;0.3;0.42;0.6;0.6;0.6;0.6]; %steep climb
bathtub_array = [bathtub_1,bathtub_2,bathtub_3];

%Generate levels & trials for experiment
num_rhohat1 = length(rhohat_1_vector);
num_rhohat1_2delta = length(rhohat1_2delta_vector);
num_k = length(k_vector);
num_lambda_1 = length(lambda_1_vector);
nun_Vhatdelta = length(Vhatdelta_vector);
nun_D_0 = length(D_0_vector);
nun_q = length(q_vector);
nun_L = length(L_vector);
nun_P = length(P_vector);
nun_eta = length(bathtub_vector);

levels = [num_rhohat1, num_rhohat1_2delta, num_k, num_lambda_1, num_Vhatdelta,
num_D_0, num_q, num_L, num_P, num_eta];
trials = fullfact(levels);
nun_trials = size(trials,1);

%SET VARIABLE INPUTS

num_lambda_1 = length(lambda_1_vector);
nun_Vhatdelta = length(Vhatdelta_vector);
nun_D_0 = length(D_0_vector);
nun_q = length(q_vector);
nun_L = length(L_vector);
nun_P = length(P_vector);
nun_eta = length(bathtub_vector);

levels = [num_rhohat1, num_rhohat1_2delta, num_k, num_lambda_1, num_Vhatdelta,
num_D_0, num_q, num_L, num_P, num_eta];
trials = fullfact(levels);
nun_trials = size(trials,1);

%SET VARIABLE INPUTS

game_calc_NEoutput = zeros(1,30);
game_calc_trialsoutput = zeros(1,17);
b_append = zeros(1,48);
temp = 1;
while temp <= nun_trials

%Pull values for trial from vectors
rhohat_1 = rhohat_1_vector(1,trials(temp,1));
rhohat1_2delta = rhohat1_2delta_vector(1,trials(temp,2));
k = k_vector(1,trials(temp,3));
lambda_1 = lambda_1_vector(1,trials(temp,4));
Vhatdelta = Vhatdelta_vector(1,trials(temp,5));
D_0 = D_0_vector(1,trials(temp,6));
q = q_vector(1,trials(temp,7));
L = L_vector(1,trials(temp,8));
P = P_vector(1,trials(temp,9));
bathtub = bathtub_vector(:,trials(temp,10));

%Convert vector values to input values
rhohat_2 = rhohat_1 + rhohat1_2delta;
Vhat = V_0 + Vhatdelta;

%Define variable inputs
variable = [rhohat_1; rhohat_2; k; lambda_1; Vhat; D_0; q; L; P;
bathtub];
[NaN_check, num_NE, NE_payoffs, NE_actions, dominant, NE_inputs,
NE_extras, u1, u2, b] = game_calc(fixed, variable);
if num_NE>0
    trial_num = temp*ones(num_NE,1);
u1_NaN = NaN_check(1,1)*ones(num_NE,1);
u2_NaN = NaN_check(1,2)*ones(num_NE,1);
num_NEarray = num_NE*ones(num_NE,1);
dominant_array =
    [dominant(1,1).*ones(num_NE,1),dominant(1,2).*ones(num_NE,1)];
end
if num_NE==0
    trial_num = temp*ones(1,1);
u1_NaN = NaN_check(1,1)*ones(1,1);
u2_NaN = NaN_check(1,2)*ones(1,1);
num_NEarray = num_NE*ones(1,1);
dominant_array = [dominant(1,1).*ones(1,1),dominant(1,2).*ones(1,1)];
end

b_append = [b_append; b];

game_calc_NEoutput = [game_calc_NEoutput; trial_num, u1 NaN, u2 NaN, num_NEarray, NE_payoffs, NE_actions, dominant_array, NE_inputs, NE_extras];

% output table
variable=variable(1:10,1);
game_calc_trialsoutput = [game_calc_trialsoutput; temp, fixed', variable', num_NE];
if mod(temp,100) == 0
    status = temp
end

temp = temp+1;
end

game_calc_NEoutput = game_calc_NEoutput(2:end,:);
game_calc_trialsoutput = game_calc_trialsoutput(2:end,:);
save('game_calc_NEoutput.dat','game_calc_NEoutput', '-ascii', '-double');
save('game_calc_trialsoutput','game_calc_trialsoutput', '-ascii', '-double');

save('b_append','b_append', '-ascii', '-double');
status = 'DONE!'

Game I game_calc.m

function [NaN_check, num_NE, NE_payoffs, NE_actions, dominant, NE_inputs, NE_extras, u1, u2, b] = game_calc(fixed, variable)

% SET INPUTS
max_horizon = fixed(1,1);
tauhat_1 = fixed(2,1);
tauhat_2 = fixed(3,1);
R_0 = fixed(4,1);
V_0 = fixed(5,1);
rhohat_1 = variable(1,1);
rhohat_2 = variable(2,1);
k = variable(3,1);
lambda_1 = variable(4,1);
Vhat = variable(5,1);
D_0 = variable(6,1);
q = variable(7,1);
L = variable(8,1);
P = variable(9,1);
bathtub_level=variable(10,1);
bathtub = variable(11:end,1);

% DEFINE ACTION SPACE
theta_set = 3:3:72;
size_theta = length(theta_set);
rho_set = 0:3:max_horizon;
size_rho = length(rho_set);
rho_set = repmat(rho_set,length(theta_set),1);
rho_set = reshape(rho_set,1,size_rho*size_theta);
A1 = [repmat(theta_set,1,size_rho);rho_set];
A1 = A1';

% remove actions where rho >= theta
[i0,j0] = find(A1(:,2)<A1(:,1));
A1_new = zeros(length(i0),2);
temp = 1;
while temp <= length(i0)
    A1(temp, 2) = A1(i0(temp),2);
    A1(temp, 1) = A1(i0(temp),1);
    A1_new(temp,1) = A1(i0(temp),1);
    A1_new(temp,2) = A1(i0(temp),2);
    temp = temp+1;
end
A1 = A1_new;

omega_set = 1:1:max_horizon;
A2 = omega_set';
size_A2 = length(A2);
size_A1 = length(A1);

theta = repmat(A1(:,1),1,size_A2);
rho = repmat(A1(:,2),1,size_A2);

omega = repmat(A2',size_A1,1);
check_omega = size(omega);
size_actions = check_omega;
action_ones = ones(size_actions(1,1),size_actions(1,2));
V_0 = repmat(V_0,size_actions(1,1),size_actions(1,2));
Vhat = repmat(Vhat,size_actions(1,1),size_actions(1,2));
theta1 = zeros(size_actions(1,1),size_actions(1,2));
theta2 = max(max(theta));
theta2 = repmat(theta2,size_actions(1,1),size_actions(1,2));
V = V_0 + ((V_0 - Vhat)./(theta1 - theta2)).*theta;
D_0 = repmat(D_0,size_actions(1,1),size_actions(1,2));
P = repmat(P,size_actions(1,1),size_actions(1,2));
b = (log((action_ones+V)./D_0))./(log(L./P));

% DEFINE MANUFACTURER PAYOFF
% Define probability of leaving
Pr_leavelookup = [theta_set', bathtub];
Pr_leave = zeros(size_actions(1,1),size_actions(1,2));
temp_i = 1;
temp_j = 1;
while temp_i <= size_actions(1,1)
    while temp_j <= size_actions(1,2)
        [bathtubi, bathtubj] = find(Pr_leavelookup(:,1)==theta(temp_i,temp_j));
        Pr_leave(temp_i,temp_j) = Pr_leavelookup(bathtubi,2);
        temp_j = temp_j+1;
    end
    temp_i = temp_i+1;
end
end
    temp_i = temp_i+1;
    temp_j = 1;
end

%Define lambda1, lambda2_bar, and lambda_2 for adoption time pdf
lambda_1 = repmat(lambda_1,size_A1, size_A2);
tauhat_1 = repmat(tauhat_1,size_A1, size_A2);
tauhat_2 = repmat(tauhat_2,size_A1, size_A2);
k = repmat(k,size_A1, size_A2);
rhohat_1 = repmat(rhohat_1,size_A1, size_A2);
rhohat_2 = repmat(rhohat_2,size_A1, size_A2);

lambda_2bar = ((tauhat_2./omega) - ones(size(lambda_1))).*lambda_1.*k;

[i1,j1] = find(rho<=rhohat_1); %Defining breakpoints for piecewise lambda_2 function
[i2,j2] = find(rho>=rhohat_2);
lambda2_break1 = max(i1); %rows <= this # in matrix are 1st piece
lambda2_break2 = min(i2); %rows >= this # in matrix are 3rd piece
size_lambda2_break2 = size(lambda2_break2);
lambda_2 = zeros(size(lambda_1));
if size_lambda2_break2(1,1) == 0
    lambda2_break2 = size(lambda_1,1);
end
%piece 1 for lambda2
lambda_2(1:lambda2_break1,:) = lambda_2bar(1:lambda2_break1,:);

%piece 2 for lambda2
rho_temp = rho(lambda2_break1:lambda2_break2,:);
omega_temp = omega(lambda2_break1:lambda2_break2,:);
rhohat_1_temp = rhohat_1(lambda2_break1:lambda2_break2,:);
rhohat_2_temp = rhohat_2(lambda2_break1:lambda2_break2,:);
lambda_2bar_temp = lambda_2bar(lambda2_break1:lambda2_break2,:);
tauhat_2_temp = tauhat_2(lambda2_break1:lambda2_break2,:);
ones_temp = ones(size(lambda_2bar(lambda2_break1:lambda2_break2,:)));
numerator_temp = (lambda_2bar_temp - ((tauhat_2_temp./omega_temp) - ones_temp).*lambda_1_temp);
denominator_temp = rhohat_1_temp - rhohat_2_temp;
lambda_2(lambda2_break1:lambda2_break2,:) = ((numerator_temp./denominator_temp).*((rho_temp - rhohat_1_temp))+lambda_2bar_temp);

%piece 3 for lambda2
if lambda2_break2 ~= size(lambda_1,1)
    temp = size(tauhat_2(lambda2_break2:end,:));
    lambda_2(lambda2_break2:end,:) =
    ((tauhat_2(lambda2_break2:end,:)/omega(lambda2_break2:end,:)) - ones(temp(1,1), temp(1,2))).*lambda_1(lambda2_break2:end,:);
end
\[ \text{rhohat_slope} = \frac{\lambda_2 - \left( \frac{\tauhat_2}{\omega} \right)}{\text{ones(size(lambda_2bar)).*lambda_1}} / (\text{rhohat_1} - \text{rhohat_2}); \]

% Calculate ul
\[ \text{Pr_time} = \text{betacdf}((\text{rho} - \tauhat_1), (\text{tauhat_2} - \tauhat_1), \lambda_1, \lambda_2); \]
\[ \text{ul} = \text{Pr_time}.*\text{V} - \text{Pr_leave}.*\text{V}; \]
\[ \text{ul} = \text{round}((\text{ul}.*10000000000000000)./10000000000000000); \]
\[ \text{NaN_check} = \text{zeros}(1,2); \]
\[ \text{ul}_\text{NaN} = \text{isnan}((\text{ul})); \]
\[ \text{NaN_check}(1,1) = \text{sum(sum(ul}_\text{NaN}); \]

% DEFINE PHYSICIAN PAYOFF

% Define D
\[ q = \text{repmat}(q, \text{size_actions}(1,1), \text{size_actions}(1,2)); \]

\[ [i3,j3] = \text{find}(\omega < ((\text{ones(size_actions(1,1), size_actions(1,2)} - D_0)./q)); \]

% Defining breakpoints for piecewise D function
\[ D\text{break} = \text{max}(j3); \]
\[ D = \text{zeros(size_actions);} \]
\[ D(:,1:D\text{break}) = D_0(:,1:D\text{break}) + q(:,1:D\text{break}).*\omega(:,1:D\text{break}); \]
\[ D(:,D\text{break}+1:end) = 1; \]

% Define x1 binary variable
\[ x1 = \text{zeros(size_actions(1,1), size_actions(1,2));} \]

\[ [i4,j4] = \text{find}(\rho < \omega); \]
\[ \text{temp} = 1; \]
\[ \text{while temp} \leq \text{length(i4)} \]
\[ \quad x1(i4(temp), j4(temp)) = 1; \]
\[ \quad \text{temp} = \text{temp}+1; \]
\[ \text{end} \]

% Define x2 binary variable
\[ x2 = \text{zeros(size_actions(1,1), size_actions(1,2));} \]

\[ [i5,j5] = \text{find}(\theta + \rho < ((\text{ones(size_actions(1,1), size_actions(1,2) + V)}./D_0) - (D0^((\text{ones(size_actions(1,1), size_actions(1,2) - 0)}.^((\text{ones(size_actions(1,1), size_actions(1,2))./b}) - ((D0^((\text{ones(size_actions(1,1), size_actions(1,2) - 0))./b}) + \omega));} \]
\[ \text{temp} = 1; \]
\[ \text{while temp} \leq \text{length(i5)} \]
\[ \quad x2(i5(temp), j5(temp)) = 1; \]
\[ \quad \text{temp} = \text{temp}+1; \]
\[ \text{end} \]

% Define limit 1
\[ \text{lim}_1 = (x1.*\rho) + ((\text{action_ones}-x1).*\omega); \]

% Define limit 2
\[ \text{maxval}_\text{pt} = ((\text{action_ones} + V)./(D_0).^((\text{action_ones})./b)) - ((D_0^((\text{action_ones})./b)) + \omega); \]
\[ \text{lim}_2 = (x1.*\rho) + ((\text{action_ones}-x1).*((x2.*(\theta + \rho)) + ((\text{action_ones}-x2).*\text{maxval}_\text{pt})); \]

% Define limit 3
\[ \text{lim}_3 = (x1.*\rho) + ((\text{action_ones}-x1).*((\theta + \rho)); \]
%Calculate u2
%Calculate 1st piece of E(R(tau))
R_0 = repmat(R_0,size_actions(1,1),size_actions(1,2));
ERtau_1 = lim_1.*R_0;

%Calculate 2nd piece of E(R(tau))
ERtau_2 = zeros(size_actions(1,1),size_actions(1,2));
[i6,j6] = find(lim_2-lim_1 > zeros(size_actions(1,1),size_actions(1,2)));
temp = 1;
while temp <= length(i6)
    m = i6(temp);
    n = j6(temp);
    ERtau_2(m,n) = ((D_0(m,n)*R_0(m,n)*((D(m,n)/D_0(m,n))^(1/b(m,n))-
                    omega(m,n)+lim_2(m,n))^(1+b(m,n)))/(b(m,n)+1))-
     ((D_0(m,n)*R_0(m,n)*((D(m,n)/D_0(m,n))^(1/b(m,n))-
                    omega(m,n)+lim_1(m,n))^(1+b(m,n)))/(b(m,n)+1));
temp = temp+1;
end

%Calculate 3rd piece of E(R(tau))
ERtau_3 = (lim_3 - lim_2).*(action_ones+V).*R_0;

u2 = R_0.*ones(size_actions(1,1),size_actions(1,2));
[i7,j7] = find(lim_3 ~= zeros(size_actions(1,1),size_actions(1,2)));
temp = 1;
while temp <= length(i7)
    m = i7(temp);
    n = j7(temp);
    u2(i7(temp),j7(temp)) = (1/(lim_3(i7(temp),j7(temp))))*ERtau_1(i7(temp),j7(temp))+ERtau_2(i7(temp),j7(temp)) + ERtau_3(i7(temp),j7(temp));
temp = temp+1;
end
u2 = round(u2.*1000000000000000)./1000000000000000;

%CALCULATE PURE NASH EQUILIBRIUM
dominant = zeros(1,2);
%Find max values of u1 across each player 2 actions
maxu1_xa2 = max(u1);
ulmax_mat = zeros(size_actions(1,1),size_actions(1,2));
i8=zeros(1,1);
j8=zeros(1,1);
temp = 1;
while temp <= size_actions(1,2)
    [i8_temp,j8_temp] = find(u1(:,temp) == maxu1_xa2(1,temp));
    j8_temp = temp.*j8_temp;
    i8 = [i8;i8_temp];
    j8 = [j8;j8_temp];
temp = temp + 1;
end
i8 = i8(2:end);
j8 = j8(2:end);
if i8(:,1) == i8(1,1)
dominant(1,1) = 1;
end

temp = 1;
while temp <= length(i8)
    ulmax_mat(i8(temp),j8(temp)) = u1(i8(temp),j8(temp));
    temp = temp + 1;
end

% Find max values of u2 across each player 1 actions
maxu2_xal = max(u2,[],2);
maxu2_xal = maxu2_xal';
u2max_mat = zeros(size_actions(1,1),size_actions(1,2));
i9=zeros(1,1);
j9=zeros(1,1);
temp = 1;
while temp <= size_actions(1,1)
    [i9_temp,j9_temp] = find(u2(temp,:) == maxu2_xal(1,temp));
    i9_temp = temp.*i9_temp;
    i9 = [i9,i9_temp];
    j9 = [j9,j9_temp];
    temp = temp + 1;
end
i9 = i9(2:end);
j9 = j9(2:end);
temp = 1;
if j9(1,:) == j9(1,1)
    dominant(1,2) = 1 ;
end
while temp <= length(i9)
    u2max_mat(i9(temp),j9(temp)) = u2(i9(temp),j9(temp));
    temp = temp + 1;
end

% Identify pure NE based upon u1, u2 calcs
NE_check = ulmax_mat.*u2max_mat;
i10,j10 = find(NE_check > 0);
num_NE = length(i10);
NE_payoffs = zeros(1,2);
NE_actions = zeros(1,3);
variable=variable(1:10,1);
NE_inputs = zeros(1,length(fixed)+length(variable));
NE_extras = zeros(1,4);
omega_rho_check = zeros(num_NE,1);
temp = 1;
if i10==0
    temp=0;
end
while temp <= length(i10)
    m=i10(temp);
    n=j10(temp);
    NE_payoffs = [NE_payoffs;u1(m,n), u2(m,n)];
    NE_actions = [NE_actions;theta(m,n), rho(m,n), omega(m,n)];
    if rho(m,n) <= omega(m,n), omega_rho_check(temp,1) = 1;
end
NE_extras = [NE_extras; omega_rho_check(temp,1), rhohat_2(m,n) - rhohat_1(m,n), lambda_2bar(m,n), rhohat_slope(m,n)];

NE_inputs = [NE_inputs; fixed', variable'];

temp = temp+1;
end

if size(NE_payoffs,1)~=1
    NE_payoffs = NE_payoffs(2:end,:);
    NE_actions = NE_actions(2:end,:);
    NE_inputs = NE_inputs(2:end,:);
    NE_extras = NE_extras(2:end,:);
end

Game I pareto_rank.m

%Read in file
clear
load game_calc_NEoutput.dat;

%Arrange so each trial is segmented
size_input=size(game_calc_NEoutput);
num_rows=size_input(1,1);
num_trials = max(game_calc_NEoutput(:,1));  %Calculate number of trials
trial_counter=1;
trial_NEnum=zeros(1);
itr_a=0;
while trial_counter <= num_trials    %For each trial
    itr_a=itr_a+1;
    [temp_i, temp_j]= find(game_calc_NEoutput(:,1)==trial_counter);
    trial_NEnum(itr_a,1)=max(temp_i);
    trial_counter=trial_counter+1;
end
trial_NEnum=[trial_NEnum;trial_NEnum(end)*2];
trial_NEnum_shift=[0;trial_NEnum(l:end-l,1)];
segments=trial_NEnum-trial_NEnum_shift;
[temp_i, temp_j]=size(segments);
segments=segments(1:temp_i-1, 1);
max_numNE=max(segments);
NE_cell=mat2cell(game_calc_NEoutput, segments', size_input(1,2));

%Rank NE for each trial
itr_b=1;

while itr_b<=num_trials
    %For each trial
    itr_b
    trial_matrix=cell2mat(NE_cell(itr_b));
    [size_i, size_j]=size(trial_matrix);
    temp_matrix = trial_matrix;
    temp_matrix(:,size_j+1)=zeros(size_i,1);
    trial_matrix2=zeros(1,size_j+1);
    rank=1;
num_NE=size_i;
last_flag=0;

%For subset
while last_flag==0

%rank
    temp_u1=temp_matrix(:,5);
    temp_u2=temp_matrix(:,6);
    maxu1=max(temp_u1);
    maxu2=max(temp_u2);
    maxchecku1=max(temp_u1/maxu1);
    maxchecku2=max(temp_u2/maxu2);
    maxchecku1(maxchecku1~=1)=0;
    maxchecku2(maxchecku2~=1)=0;
    rank_mat=rank*ones(length(temp_u2),1);
    Branked= maxchecku1.*maxchecku2.*rank_mat;

    if size(temp_matrix,1)==1
        if temp_matrix(1,2)==0
            last_flag=1;
        end
    end

    if sum(Branked)==0
        temp_u1(maxchecku2==0)=0;
        temp_u2(maxchecku1==0)=0;
        maxu1=max(temp_u1);
        maxu2=max(temp_u2);
        maxchecku1=max(temp_u1/maxu1);
        maxchecku2=max(temp_u2/maxu2);
        maxchecku1(maxchecku1~=1)=0;
        maxchecku2(maxchecku2~=1)=0;
        rank_mat=rank*ones(length(temp_u2),1);
        Branked= (maxchecku1+maxchecku2).*rank_mat;
    end

    temp_matrix(:,size_j+1)=temp_matrix(:,size_j+1)+Branked;

    % keep only unranked rows
    sortcol=size(temp_matrix,2);
    temp_matrix_sorted = sortrows(temp_matrix,-sortcol);
    [temp_ib, temp_jb]=find(temp_matrix_sorted(:,size_j+1)==0);

    if last_flag==0
        last_flag = isempty(temp_ib);
    end
    if last_flag==0
        min_row = min(temp_ib);
        temp_matrix=temp_matrix_sorted(min_row:end,:);
        trial_matrix2=[trial_matrix2;temp_matrix_sorted(1:min_row-1,:)] ;
    end
    if last_flag==1
        trial_matrix2=[trial_matrix2;temp_matrix_sorted(1,:)];
    end
rank=rank+1;
end
trial_matrix2 = trial_matrix2(2:end,:);
NE_cell(itr_b,1)=mat2cell(trial_matrix2);

trial_matrix2 = trial_matrix2(:,30);
itr_b=itr_b+1
end
pareto_rank_out=cell2mat(NE_cell);
save('pareto_rank_output.dat','pareto_rank_out','-ascii', '-double');

Game II Matlab Code

```
Game II full_factorial_trials.m

%SET FIXED INPUTS
max_horizon = 48;
max_theta= 72;
tauhat_1 = 0;
R_0 = 100;
V_0 = 0;
p1=0.4; %value
p2=0.4; %bathtub
etahat_L = .1;
etahat_H = 1;
fixed = [max_horizon; max_theta; tauhat_1; R_0; V_0; p1; p2; etahat_L;
etahat_H];

%DEFINE FULL FACTORIAL EXPERIMENT
%Define ranges for factors
lambda_1_vector = [1.1, 4];
Vhatdelta_vector = [.1, 1];
L_vector = [15, 75];
P_vector = [1, 10];
value_shape_vector=[1,2,3]; %1 = linear 2 = concave 3 = convex
```
bathtub_shape_vector= [1, 2, 3, 4, 5]; % 1 = none 2 = concaveL 3 = concaveH 4 = convexL 5 = convexH
D_0_vector = [.10, .75];
q_vector = [.005, .1];
a_vector = [.1, .8];

% Generate levels & trials for experiment
num_lambda_1 = length(lambda_1_vector);
num_Vhatdelta = length(Vhatdelta_vector);
num_L = length(L_vector);
num_P = length(P_vector);
num_value = length(value_shape_vector);
num_eta = length(bathtub_shape_vector);
num_D0 = length(D_0_vector);
num_q = length(q_vector);
num_a = length(a_vector);

levels = [num_lambda_1, num_Vhatdelta, num_L, num_P, num_value, num_eta, num_D0, num_q, num_a];
trials = fullfact(levels);
num_trials = size(trials, 1);

% Set variable inputs
game_calc_NEoutput = zeros(1, 29);
game_calc_trialsoutput = zeros(1, 20);
b_append = zeros(1, 48);
temp = 1;
while temp <= num_trials
    % Pull values for trial from vectors
    lambda_1 = lambda_1_vector(1, trials(temp, 1));
    Vhatdelta = Vhatdelta_vector(1, trials(temp, 2));
    L = L_vector(1, trials(temp, 3));
    P = P_vector(1, trials(temp, 4));
    value_shape = value_shape_vector(1, trials(temp, 5));
    bathtub_shape = bathtub_shape_vector(1, trials(temp, 6));
    D_0 = D_0_vector(1, trials(temp, 7));
    q = q_vector(1, trials(temp, 8));
    a = a_vector(1, trials(temp, 9));

    % Define parameters from input values
    Vhat = V_0 + Vhatdelta;
    D_0prime = a + ((1-a)*D_0);
    Lprime = (1-a)*L;

    theta_vector = 3:3:max_theta;
    theta_vector = [theta_vector];

    % Linear
    if (value_shape == 1)
        value_vector = V_0 + ((Vhat - V_0)/(max_theta-0)).*theta_vector;
    end;
    % Concave
    if (value_shape == 2)
value_vector = p1.*Vhat.*theta_vector.^(log(1/p1)/log(max_theta));
end;
%convex
if (value_shape == 3)
    value_vector = (1/((max_theta^2)/Vhat)).*theta_vector.^2  ;
end;

%none
if (bathtub_shape == 1)
    bathtub_vector = theta_vector.*0;
end;
%concave low
if (bathtub_shape == 2)
    bathtub_vector = p2.*etahat_L.*theta_vector.^(log(1/p2)/log(max_theta));
end;
%concave high
if (bathtub_shape == 3)
    bathtub_vector = p2.*etahat_H.*theta_vector.^(log(1/p2)/log(max_theta));
end;
%convex low
if (bathtub_shape == 4)
    bathtub_vector = (1/((max_theta^2)/etahat_L)).*theta_vector.^2;
end;
%convex high
if (bathtub_shape == 5)
    bathtub_vector = (1/((max_theta^2)/etahat_H)).*theta_vector.^2;
end;

%Define variable inputs
variable = [lambda_1; Vhat; Lprime; P; value_vector; bathtub_vector;
    value_shape;bathtub_shape;D_0prime; q; a ];
[NaN_check, num_NE, NE_payoffs, NE_actions, dominant, NE_inputs, u1, u2,
b] = game_calc(fixed, variable);
if num_NE>0
    trial_num = temp*ones(num_NE,1);
    u1_NaN = NaN_check(1,1)*ones(num_NE,1);
    u2_NaN = NaN_check(1,2)*ones(num_NE,1);
    num_NEarray = num_NE*ones(num_NE,1);
    dominant_array = [dominant(1,1).*ones(num_NE,1),dominant(1,2).*ones(num_NE,1)];
end
if num_NE==0
    trial_num = temp*ones(1,1);
    u1_NaN = NaN_check(1,1)*ones(1,1);
    u2_NaN = NaN_check(1,2)*ones(1,1);
    num_NEarray = num_NE*ones(1,1);
    dominant_array = [dominant(1,1).*ones(1,1),dominant(1,2).*ones(1,1)];
end
variable_out=[lambda_1; Vhat; L; P; value_shape; bathtub_shape; D_0; q; a);

b_append = [b_append; b];

game_calc_NEoutput = [game_calc_NEoutput; trial_num, u1 NaN,u2 NaN, num_NEarray, NE_payoffs, NE_actions, dominant_array, NE_inputs]; %output table
variable = [lambda_1; Vhat; L; P; value_shape; bathtub_shape;
D_0prime; q; a];

game_calc_trialsoutput = [game_calc_trialsoutput; temp, num_NE, fixed',
variable_out'];
if mod(temp,10) == 0
status = temp
end
temp = temp+1;
end

game_calc_NEoutput = game_calc_NEoutput(2:end,:);
game_calc_trialsoutput = game_calc_trialsoutput(2:end,:);
save('game_calc_NEoutput.dat','game_calc_NEoutput','-ascii','-double');
save('game_calc_trialsoutput','game_calc_trialsoutput','-ascii','-double');
save('b_append','b_append','-ascii','-double');
status = 'DONE!'

Game II game_calc.m

function [NaN_check, num_NE, NE_payoffs, NE_actions, dominant, NE_inputs, u1, u2, b] = game_calc(fixed, variable)

%SET INPUTS
%Fixed
max_horizon = fixed(1,1);
max_theta = fixed(2,1);
tauhat_1 = fixed(3,1);
R_0 = fixed(4,1);
V_0 = fixed(5,1);
pI = fixed(6,1);
p2 = fixed(7,1);
etahat_L = fixed(8,1);
etahat_H = fixed(9,1);

%Variable
%variable = [lambda_1; Vhat; L; P; value_shape; bathtub_shape];
lambda_1 = variable(1,1);
Vhat = variable(2,1);
Lprime = variable(3,1);
P = variable(4,1);
value=variable(5:5+(max_theta/3)-1);
bathtub= variable(5+(max_theta/3):52);
value_shape=variable(53,1);
bathtub_shape=variable(54,1);
D_0prime = variable(55,1);
q = variable(56,1);
a = variable(57,1);

if (1-D_0prime)/q < 1
    D_flag=1;
else D_flag=0;
end

%DEFINE ACTION SPACE
theta_set = 3:3:max_theta;
size_theta = length(theta_set);
rho_set = 0:3:max_horizon;
size_rho = length(rho_set);
rho_set = repmat(rho_set, size_theta, 1);
rho_set = reshape(rho_set, 1, size_rho*size_theta);
A1 = [repmat(theta_set, size_rho, 1); rho_set];
A1 = A1';

%remove actions where rho >= theta
[i0, j0] = find(A1(:,2)<A1(:,1));
A1_new = zeros(length(i0), 2);
while temp <= length(i0)
    A1(temp, 2) = A1(i0(temp),2);
    A1(temp, 1) = A1(i0(temp),1);
    A1_new(temp,1) = A1(i0(temp),1);
    A1_new(temp,2) = A1(i0(temp),2);
    temp = temp+1;
end
A1 = A1_new;

omega_set = 1:1:max_horizon;
A2 = omega_set';
size_A2 = length(A2);
size_A1 = length(A1);

theta = repmat(A1(:,1), size_A2, 1);
rho = repmat(A1(:,2), size_A2, 1);

omega = repmat(A2', size_A1, 1);
check_omega = size(omega);
size_actions = check_omega;

action_ones = ones(size_actions(1,1), size_actions(1,2));
Lprime = repmat(Lprime, size_actions(1,1), size_actions(1,2));
P = repmat(P, size_actions(1,1), size_actions(1,2));
D_0prime = repmat(D_0prime, size_actions(1,1), size_actions(1,2));

%Define value;
value_lookup = [theta_set', value];
V = zeros(size_actions(1,1), size_actions(1,2));
temp_i = 1;
temp_j = 1;
while temp_i <= size_actions(1,1)
    while temp_j <= size_actions(1,2)
        [valuei, valuej] = find(value_lookup(:,1)==theta(temp_i,temp_j));
        V(temp_i,temp_j) = value_lookup(valuei,2);
        temp_j = temp_j+1;
    end
    temp_i = temp_i+1;
    temp_j = 1;
end

b = (log((action_ones+V)./D_0prime))./(log(Lprime./P));

%DEFINE MANUFACTURER PAYOFF
%Define probability of leaving
Pr_leave = zeros(size_actions(1,1),size_actions(1,2));
temp_i = 1;
temp_j = 1;
while temp_i <= size_actions(1,1)
    while temp_j <= size_actions(1,2)
        [bathtubj] = find(Pr_leavelookup(:,1)==theta(temp_i,temp_j));
        Pr_leave(temp_i,temp_j) = Pr_leavelookup(bathtubj,2);
        temp_j = temp_j+1;
    end
    temp_i = temp_i+1;
end

define parameters for adoption time pdf
lambda_1 = repmat(lambda_1,size_A1, size_A2);
lambda_2 = lambda_1;
tauhat_1 = repmat(tauhat_1,size_A1, size_A2);
tauhat_2 = 2*omega;

%IF(rho<=2*omega, rho, 2*omega)
rho_le2omega = le(rho, 2*omega);
tau = (rho_le2omega.*rho) + ((1 - rho_le2omega).*2.*omega);

% Calculate ul
Pr_time = betacdf((tau-tauhat_1)/(tauhat_2-tauhat_1)),lambda_1,lambda_2);
u1 = ones(size(omega))-Pr_leave.*V;
u1 = round(u1.*1000000000000000)./1000000000000000;
NaN_check = zeros(1,2);
u1_NaN = isnan(u1);
NaN_check(1,1) = sum(sum(u1_NaN));

%DEFINE PHYSICIAN PAYOFF
%Define D
if D_flag == 0;
    q = repmat(q,size_actions(1,1),size_actions(1,2));
    [i3,j3] = find(omega<(ones(size_actions(1,1),size_actions(1,2))-D_0prime)./q));  %Defining breakpoints for piecewise D function
D_break = max(j3);
D = zeros(size_actions);
D(:,1:D_break) = D_0prime(:,1:D_break)+(q(:,1:D_break).*omega(:,1:D_break));
D(:,D_break+1:end) = 1;
else if D_flag == 1
    D = ones(size_actions);
end;

%Define x1 binary variable
x1 = zeros(size_actions(1,1),size_actions(1,2));
[i4,j4] = find(rho<omega);
temp = 1;
while temp <= length(i4)
    x1(i4(temp),j4(temp)) = 1;
    temp = temp+1;
end

%Define x2 binary variable
x2 = zeros(size_actions(1,1),size_actions(1,2));
[i5,j5] = find((theta+rho)<((((ones(size_actions(1,1),size_actions(1,2))+V)./D_0prime).^((ones(size_actions(1,1),size_actions(1,2))./b))-(D./D_0prime).^((ones(size_actions(1,1),size_actions(1,2))./b)))+omega));
temp = 1;
while temp <= length(i5)
    x2(i5(temp),j5(temp)) = 1;
    temp = temp+1;
end

%Define limit 1
lim_1 = (x1.*rho)+((action_ones-x1).*omega);

%Define limit 2
maxval_pt = (((action_ones+V)./D_0prime).^((action_ones.b))-(D./D_0prime).^((action_ones.b))+omega);
lim_2 = (x1.*rho)+(action_ones-x1).*((x2.*(theta+rho))+((action_ones-x2).*maxval_pt));

%Define limit 3
lim_3 = (x1.*rho)+((action_ones-x1).*theta+rho));

%Calculate u2
%Calculate 1st piece of E(R(tau))
R_0 = repmat(R_0,size_actions(1,1),size_actions(1,2));
ERtau_1 = lim_1.*R_0;

%Calculate 2nd piece of E(R(tau))
ERtau_2 = zeros(size_actions(1,1),size_actions(1,2));
[i6,j6] = find(lim_2-lim_1 > zeros(size_actions(1,1),size_actions(1,2)));
temp = 1;
%((R0*(1-omega+lim2)^(1+b))/(1+b))-((R0*(1-omega+lim 1)^(1+b))/(1+b))
while temp <= length(i6)
m = i6(temp);
n = j6(temp);
ERtau_2(m,n) =
((D_0prime(m,n)*R_0(m,n)*((D(m,n)/D_0prime(m,n))^(1/b(m,n)) -
omega(m,n)+lim_2(m,n))/(b(m,n)+1)) -
((D_0prime(m,n)*R_0(m,n)*((D(m,n)/D_0prime(m,n))^(1/b(m,n)) -
omega(m,n)+lim_1(m,n))/(b(m,n)+1));
temp = temp+1;
end

%Calculate 3rd piece of E(R(tau))
ERtau_3 = (lim_3 - lim_2).*(action_ones+V).*R_0;

%u2
u2 = R_0.*ones(size_actions(1,1),size_actions(1,2));
[i7,j7] = find(lim_3 ~= zeros(size_actions(1,1),size_actions(1,2)));
temp = 1;
while temp <= length(i7)
u2(i7(temp),j7(temp)) =
(1/(lim_3(i7(temp),j7(temp))))*(ERtau_1(i7(temp),j7(temp))+ERtau_2(i7(temp),j7(temp)) + ERtau_3(i7(temp),j7(temp)));
temp = temp+1;
end
u2 = round(u2.*1000000000000000)/1000000000000000;
u2_NaN = isnan(u2);
NaN_check(1,2) = sum(sum(u2_NaN));

%CALCULATE PURE NASH EQUILIBRIUM
dominant = zeros(1,2);
%Find max values of u1 across each player 2 actions
maxul_xa2 = max(u1);
ulmax_mat = zeros(size_actions(1,1),size_actions(1,2));
i8=zeros(1,1);
j8=zeros(1,1);
temp = 1;
while temp <= size_actions(1,2)
[i8_temp,j8_temp] = find(u1(:,temp) == maxul_xa2(1,temp));
j8_temp = temp.*j8_temp;
i8 = [i8;i8_temp];
j8 = [j8;j8_temp];
temp = temp + 1;
end
i8 = i8(2:end);
j8 = j8(2:end);

if i8(:,1) == i8(1,1)
dominant(1,1) = 1;
end

temp = 1;
while temp <= length(i8)
ulmax_mat(i8(temp),j8(temp)) = u1(i8(temp),j8(temp));
temp = temp + 1;
end
%Find max values of u2 across each player 1 actions
maxu2_xa1 = max(u2,[],2);
maxu2_xa1 = maxu2_xa1';
u2max_mat = zeros(size_actions(1,1),size_actions(1,2));
i9=zeros(1,1);
j9=zeros(1,1);
temp = 1;
while temp <= size_actions(1,1)
    [i9_temp,j9_temp] = find(u2(temp,:) == maxu2_xa1(1,temp));
    i9_temp = temp.*i9_temp;
    i9 = [i9,i9_temp];
    j9 = [j9,j9_temp];
    temp = temp + 1;
end
i9 = i9(2:end);
j9 = j9(2:end);
temp = 1;
if j9(1,:) == j9(1,1)
dominant(1,2) = 1 ;
end
while temp <= length(i9)
    u2max_mat(i9(temp),j9(temp)) = u2(i9(temp),j9(temp));
    temp = temp + 1;
end

%Identify pure NE based upon u1, u2 calcs
NE_check = u1max_mat.*u2max_mat;
[i10,j10] = find(NE_check > 0);
num_NE = length(i10);
NE_payoffs = zeros(1,2);
NE_actions = zeros(1,3);
variable_out=[variable(1:4,1); variable(53,1);variable(54,1); variable(55,1);
variable(56,1); variable(57,1)];
NE_inputs = zeros(1,length(fixed)+length(variable_out));

omega_rho_check = zeros(num_NE,1);
temp = 1;
if i10==0
    temp=0;
end
while temp <= length(i10)
    m=i10(temp);
    n=j10(temp);
    NE_payoffs = [NE_payoffs;u1(m,n), u2(m,n)];
    NE_actions = [NE_actions;theta(m,n), rho(m,n), omega(m,n)];
    NE_inputs = [NE_inputs;fixed', variable_out'];
    temp = temp+1;
end
if size(NE_payoffs,1)~=1
    NE_payoffs = NE_payoffs(2:end,:);
    NE_actions = NE_actions(2:end,:);
NE_inputs = NE_inputs(2:end,:);
end

Game II pareto_rank.m

%Read in file
clear
load game_calc_NEoutput.dat;

%Arrange so each trial is segmented
size_input=size(game_calc_NEoutput);
num_rows=size_input(1,1);
num_trials = max(game_calc_NEoutput(:,1));  %Calculate number of trials
trial_counter=1;
trial_NEnum=zeros(1);
itr_a=0;
while trial_counter <= num_trials  %For each trial
    itr_a=itr_a+1;
    [temp_i, temp_j]= find(game_calc_NEoutput(:,1)==trial_counter);
    trial_NEnum(itr_a,1)=max(temp_i);
    trial_counter=trial_counter+1;
end
trial_NEnum=[trial_NEnum;trial_NEnum(end)*2];
trial_NEnum_shift=[0;trial_NEnum(1:end-1,1)];
segments=trial_NEnum-trial_NEnum_shift;
[temp_i, temp_j]=size(segments);
segments=segments(1:temp_i-1, 1);
max_numNE=max(segments);
NE_cell=mat2cell(game_calc_NEoutput, segments', size_input(1,2));

%Rank NE for each trial
itr_b=1;
while itr_b<=num_trials
    %For each trial
    itr_b
    trial_matrix=cell2mat(NE_cell(itr_b));
    [size_i, size_j]=size(trial_matrix);
    temp_matrix = trial_matrix;
    temp_matrix(:,size_j+1)=zeros(size_i,1);
    trial_matrix2=zeros(1,size_j+1);
    rank=1;
    num_NE=size_i;
    last_flag=0;
    %For subset
    while last_flag==0
        %rank
        temp_u1=temp_matrix(:,5);
        temp_u2=temp_matrix(:,6);
        maxu1=max(temp_u1);
        maxu2=max(temp_u2);
        maxchecku1=temp_u1/maxu1;
        maxchecku2=temp_u2/maxu2;
        last_flag=0;
        %For each NE in trial
        for i = 1:num_NE
            if maxchecku1(i) > maxchecku2(i)
                %Rank NE
                trial_matrix2(rank)=i;
                rank=rank+1;
                last_flag=1;
            end
        end
    end
end

%Data manipulation and analysis

%Output
disp('Game II Pareto Rank
');
disp('Trial NEnum:
');
disp(trial_NEnum);
disp('Segments:
');
disp(segments);
disp('Max NE:
');
disp(max_numNE);
disp('NE Cell:
');
disp(NE_cell);

maxchecku2=temp_u2/maxu2;
maxchecku1(maxchecku1~=1)=0;
maxchecku2(maxchecku2~=1)=0;
rank_mat=rank*ones(length(temp_u2),1);
Branked= maxchecku1.*maxchecku2.*rank_mat;

if size(temp_matrix,1)==1
    if temp_matrix(1,2)==0
        last_flag=1;
    end
end

if sum(Branked)==0
    temp_u1(maxchecku2==0)=0;
    temp_u2(maxchecku1==0)=0;
    maxu1=max(temp_u1);
    maxu2=max(temp_u2);
    maxchecku1=temp_u1/maxu1;
    maxchecku2=temp_u2/maxu2;
    maxchecku1(maxchecku1~=1)=0;
    maxchecku2(maxchecku2~=1)=0;
    rank_mat=rank*ones(length(temp_u2),1);
    Branked= (maxchecku1+maxchecku2).*rank_mat;
end

temp_matrix(:,size_j+1)=temp_matrix(:,size_j+1)+Branked;

% keep only unranked rows
sortcol=size(temp_matrix,2);
temp_matrix_sorted = sortrows(temp_matrix,-sortcol);
[temp_ib, temp_jb]=find(temp_matrix_sorted(:,size_j+1)==0);

    if last_flag==0
        last_flag = isempty(temp_ib);
    end
    if last_flag==0
        min_row = min(temp_ib);
        temp_matrix=temp_matrix_sorted(min_row:end,:);
        trial_matrix2=[trial_matrix2;temp_matrix_sorted(1:min_row-1,:)]
    end
    if last_flag==1
        trial_matrix2=[trial_matrix2;temp_matrix_sorted(1,:)]
    end

    rank=rank+1;
end
trial matrix2 = trial matrix2(2:end,:);
NE_cell(itr_b,1)=mat2cell(trial_matrix2);

trial_matrix2 = trial_matrix2(:,26);
itr_b=itr_b+1
end
pareto_rank_out=cell2mat(NE_cell);
save('pareto_rank_output.dat','pareto_rank_out','-ascii', '-double');
Game III Matlab Code

Game III full_factorial_trial.m

%SET FIXED INPUTS
max_horizon = 48;
max_theta = 72;
tauhat_l = 0;
R_0 = 100;
V_0 = 0;
p1 = 0.4; %value
p2 = 0.4; %bathtub
etahat_L = .1;
etahat_H = 1;

fixed = [max_horizon; max_theta; tauhat_l; R_0; V_0; p1; p2; etahat_L;
etahat_H];

%DEFINE FULL FACTORIAL EXPERIMENT
%Define ranges for factors
lambda_1_vector = [.4];
Vhatdelta_vector = [.1, 1];
L_vector = [15, 75];
P_vector = [1, 10];
value_shape_vector = [1, 2, 3]; %1 = linear 2 = concave 3 = convex
bathtub_shape_vector = [1, 2, 3, 4, 5]; %1 = none 2 = concaveL 3 = concaveH 4 = convexL 5 = convexH
D_0_vector = [.1];
q_vector = [.005, .1];
a_vector = [.8];
alpha_vector = [.25, .5, .75];
delta_vector = [-.25, 0, .25];
HofV_thetamax_vector = [.1, 1];
V_claimed_min_vector = [.1];

% Generate levels & trials for experiment
num_lambda_1 = length(lambda_1_vector);
num_Vhatdelta = length(Vhatdelta_vector);
num_L = length(L_vector);
num_P = length(P_vector);
num_value = length(value_shape_vector);
num_eta = length(bathtub_shape_vector);
num_D0 = length(D_0_vector);
num_q = length(q_vector);
num_a = length(a_vector);
num_alpha = length(alpha_vector);
num_delta = length(delta_vector);
num_HofV_thetamax = length(HofV_thetamax_vector);
num_V_claimed_min = length(V_claimed_min_vector);

levels = [num_lambda_1,num_Vhatdelta, num_L, num_P, num_value, num_eta, num_D0, num_q, num_a, num_alpha, num_delta, num_HofV_thetamax, num_V_claimed_min];
trials = fullfact(levels);
num_trials = size(trials,1)

% Set variable inputs
ffe_output=zeros(1,34);
temp = 1;
cumulative_num_NE=0;
while temp <= num_trials

% Pull values for trial from vectors
lambda_1 = lambda_1_vector(1,trials(temp,1));
Vhatdelta = Vhatdelta_vector(1,trials(temp,2));
L = L_vector(1,trials(temp,3));
P = P_vector(1,trials(temp,4));
value_shape = value_shape_vector(1,trials(temp,5));
bathtub_shape = bathtub_shape_vector(1,trials(temp,6));
D_0 = D_0_vector(1,trials(temp,7));
q = q_vector(1,trials(temp,8));
a = a_vector(1,trials(temp,9));
alpha = alpha_vector(1,trials(temp,10));
delta = delta_vector(1,trials(temp,11));
HofV_thetamax = HofV_thetamax_vector(1,trials(temp,12));
V_claimed_min = V_claimed_min_vector(1,trials(temp,13));

% Define parameters from input values
Vhat = V_0 + Vhatdelta;
D_0prime = a + ((1-a)*D_0);
Lprime = (1-a)*L;
if Vhat == .1
    V_claimed_min = .01;
end;

theta_vector = 3:3:max_theta;
theta_vector = theta_vector';
\%linear
if (value_shape == 1)
    value_vector = V_0 + ((Vhat - V_0) / (max_theta - 0)) * theta_vector;
end;
\%concave
if (value_shape == 2)
    value_vector = p1 * Vhat * theta_vector.^(\log(1/p1)/\log(max_theta));
end;
\%convex
if (value_shape == 3)
    value_vector = (1/((max_theta^2)/Vhat)).*theta_vector.^2;
end;

\%none
if (bathtub_shape == 1)
    bathtub_vector = theta_vector.*0;
end;
\%concave low
if (bathtub_shape == 2)
    bathtub_vector = p2.*etahat_L.*theta_vector.^((\log(1/p2)/\log(max_theta)));
end;
\%concave high
if (bathtub_shape == 3)
    bathtub_vector = p2.*etahat_H.*theta_vector.^((\log(1/p2)/\log(max_theta)));
end;
\%convex low
if (bathtub_shape == 4)
    bathtub_vector = (1/((max_theta^2)/etahat_L)).*theta_vector.^2;
end;
\%convex high
if (bathtub_shape == 5)
    bathtub_vector = (1/((max_theta^2)/etahat_H)).*theta_vector.^2;
end;

\%Define variable inputs for output
variable = [\lambda_1; Vhat; Lprime; P; value_vector; bathtub_vector;
            value_shape; bathtub_shape; D_0prime; q; a; alpha; delta; HofV_thetamax;
            V_claimed_min ];
variable_out= [\lambda_1; Vhat; Lprime; P;
               value_shape; bathtub_shape; D_0prime; q; a; alpha; delta; HofV_thetamax;
               V_claimed_min ];

[num_NE, NaN_flag, b_flag, LP_flag, Vtilde_flag, dominant, NE_A1, NE_A2,
NE_A3, NE_u1, NE_u2, NE_u3, NE_scA, NE_scB, NE_scC, NE_scD] =
threep_game_calc(fixed, variable);
cumulative_num_NE=cumulative_num_NE+num_NE;
num_rows=num_NE;
if num_NE == 0
cumulative_num_NE=cumulative_num_NE+1;
num_rows=1;
end
trial_number = temp*1;

%replicate output for number of NE
trial_num_array = repmat(trial_number, num_rows, 1);
num_NE_array = repmat(num_NE, num_rows, 1);
NaN_flag_array = repmat(NaN_flag, num_rows, 1);
b_flag_array = repmat(b_flag, num_rows, 1);
LP_flag_array = repmat(LP_flag, num_rows, 1);
dominant_array = repmat(dominant, num_rows, 1);
fixed_array = repmat(fixed, num_rows, 1);
variable_out_array = repmat(variable_out, num_rows, 1);

trial_summary = [trial_number, num_NE];
trial_output = [trial_num_array, num_NE_array, NE_scA, NE_scB, NE_scC, NE_scD, NaN_flag_array, b_flag_array, LP_flag_array, dominant_array, NE_A1, NE_A2, NE_A3, NE_u1, NE_u2, NE_u3, fixed_array, variable_out_array];

num_columns = size(trial_output, 2);

first_row = cumulative_num_NE - num_rows + 1;
last_row = cumulative_num_NE;
ffe_output(first_row:last_row,:) = trial_output;
ffe_summary(trial_number,:) = trial_summary;
trial_output = [];
trial_summary = [];
temp = temp + 1;
end;
cumulative_num_NE;
status = 'DONE!'

Game III threep_game_calc.m

function [num_NE, NaN_flag, b_flag, LP_flag, Vtilde_flag, dominant, NE_A1, NE_A2, NE_A3, NE_u1, NE_u2, NE_u3, NE_scA, NE_scB, NE_scC, NE_scD] = threep_game_calc(fixed, variable)

%DEFINE ACTION SPACE
%Define actions for player 1;
max_horizon = fixed(1,1);
max_theta = fixed(2,1);
theta_set = 3:3:max_theta;
size_theta = length(theta_set);
rho_set = 0:3:max_horizon;
size_rho = length(rho_set);
rho_set = repmat(rho_set, length(theta_set), 1);
rho_set = reshape(rho_set, 1, size_rho*size_theta);
A1 = [repmat(theta_set, 1, size_rho); rho_set];
A1 = A1';
%remove actions where rho >= theta
[i0, j0] = find(A1(:,2) < A1(:,1));
A1_new = zeros(length(i0), 2);
temp = 1;
while temp <= length(i0)
    A1(temp, 2) = A1(i0(temp), 2);
    A1(temp, 1) = A1(i0(temp), 1);
    A1_new(temp, 1) = A1(i0(temp), 1);
    A1_new(temp, 2) = A1(i0(temp), 2);
    temp = temp + 1;
end
A1 = A1_new;

% Define actions for player 2;
omega_set = 1:1:max_horizon;
A2 = omega_set';
size_A1 = length(A1);
size_A2 = length(A2);
theta = repmat(A1(:, 1), 1, size_A2);
rho = repmat(A1(:, 2), 1, size_A2);
omega = repmat(A2', size_A1, 1);
check_omega = size(omega);
size_actions = check_omega;
action_ones = ones(size_actions(1, 1), size_actions(1, 2));

% Define actions for player 3;
R_0 = fixed(4, 1);
kappa_set = (0.05:0.25:1.30);
A3 = kappa_set';
size_A3 = length(A3);

itr = 1;

% Set up dummy arrays
ui_NaN_flag = zeros(1, size_A3);
b_check_flag = zeros(1, size_A3);
LP_check_flag = zeros(1, size_A3);
u1_cube = zeros(size_A1, size_A2, size_A3);
u2_cube = zeros(size_A1, size_A2, size_A3);
u3_cube = zeros(size_A1, size_A2, size_A3);
scA_cube = zeros(size_A1, size_A2, size_A3);
scB_cube = zeros(size_A1, size_A2, size_A3);
scC_cube = zeros(size_A1, size_A2, size_A3);
scD_cube = zeros(size_A1, size_A2, size_A3);
NE_2p_cube = zeros(size_A1, size_A2, size_A3);
max_u3_check_cube = zeros(size_A1, size_A2, size_A3);
NE_3p_check_cube = zeros(size_A1, size_A2, size_A3);

while itr <= size_A3
    % Calculate payoff functions for given value of kappa;
    kappa = kappa_set(1, itr);
    [NaN_check, dominant, log_LP, b, V_claimed, u1, u2, u3, NE_check_2p,
     scenarioA, scenarioB, scenarioC, scenarioD] = payoff_calc(fixed, variable,
     theta, rho, omega, kappa, action_ones, theta_set, size_actions, size_A1,
     size_A2);

    % Check for calculation issues;
    ui_NaN_flag(1, itr) = sum(NaN_check);
    if ui_NaN_flag > 0
ui_NaN_flag=ui_NaN_flag;
end;

b_check=b<0;
b_check_flag(1,itr) = sum(sum(b_check));
if b_check_flag > 0
    b_check_flag=b_check_flag;
end;

LP_check = log_LP == 0;
LP_check_flag(1,itr)= sum(sum(LP_check));
if LP_check_flag > 0
    LP_check_flag=LP_check_flag;
end;

Vtilde_flag=0;
Vtilde_check=V_claimed<0;
Vtilde_check_flag(1,itr) = sum(sum(Vtilde_check));
if Vtilde_check_flag > 0
    Vtilde_flag=sum(Vtilde_check_flag);
end;

%Convert 2p NE output to input for 3p calculation;
%NE_2p_cube = NE_check_2p.*repmat(kappa,size_A1,size_A2);

%Add output to cubes for each kapp itr
scA_cube(:,:,itr)=scenarioA;
scB_cube(:,:,itr)=scenarioB;
scC_cube(:,:,itr)=scenarioC;
scD_cube(:,:,itr)=scenarioD;
u1_cube(:,:,itr)=u1; %u1 for 3p action space
u2_cube(:,:,itr)=u2; %u2 for 3p action space
u3_cube(:,:,itr)=u3; %u3 for 3p action space
NE_2p_cube(:,:,itr)=NE_check_2p; %check for u1 & u2 choices
itr=itr+1;
end

NaN_flag=sum(ui_NaN_flag);
b_flag=sum(b_check_flag);
LP_flag=sum(LP_check_flag);

%Find player 3 best responses;
max_u3= max(u3_cube,[],3);
itr=1;
while itr <= size_A3
    max_u3_check_cube(:,:,itr)=u3_cube(:,:,itr) == max_u3;
    itr=itr+1;
end

all_cells = zeros(size_A3,1);
no_cells = zeros(size_A3,1);
itr=1;
while itr <= size_A3
    if sum(sum(max_u3_check_cube(:, :, itr))) == numel(action_ones);
        all_cells(itr) = 1;
        noCells(itr) = 0;
    end;
    if sum(sum(max_u3_check_cube(:,:,itr))) == 0
        all_cells(itr) = 0;
        no_cells(itr) = 1;
    end;
    itr=itr+1;
end

A3_dominant_check = all_cells - no_cells;
if A3_dominant_check == 1
    dominant(1,3) = 1;
end;

% Find NE
NE_3p_check_cube = max_u3_check_cube.*NE_2p_cube; % ID NE
ind = find(NE_3p_check_cube); % Get linear index for NE
% linear index counts cells by columns, then rows, then z
% [1,3;2,4] [5,7;6,8]

[X1, Y1, Z1] = ind2sub(size(NE_3p_check_cube), ind);
num_NE = length(X1);
if num_NE ~= 0
    % Lookup NE actions
    NE_A1 = A1(X1,:);
    NE_A2 = A2(Y1,1);
    NE_A3 = A3(Z1,1);

    % Lookup NE payoffs
    itr = 1;
    NE_u1 = zeros(num_NE,1);
    NE_u2 = zeros(num_NE,1);
    NE_u3 = zeros(num_NE,1);
    NE_scA = zeros(num_NE,1);
    NE_scB = zeros(num_NE,1);
    NE_scC = zeros(num_NE,1);
    NE_scD = zeros(num_NE,1);
    while itr <= num_NE
        NE_u1(itr,1) = u1_cube(X1(itr), Y1(itr), Z1(itr));
        NE_u2(itr,1) = u2_cube(X1(itr), Y1(itr), Z1(itr));
        NE_u3(itr,1) = u3_cube(X1(itr), Y1(itr), Z1(itr));
        NE_scA(itr,1) = scA_cube(X1(itr), Y1(itr), Z1(itr));
        NE_scB(itr,1) = scB_cube(X1(itr), Y1(itr), Z1(itr));
        NE_scC(itr,1) = scC_cube(X1(itr), Y1(itr), Z1(itr));
        NE_scD(itr,1) = scD_cube(X1(itr), Y1(itr), Z1(itr));
    end

itr=itr+1;
end;
end;

if num_NE==0
    NE_A1=[0,0];
    NE_A2=0;
    NE_A3=0;
    NE_u1=0;
    NE_u2=0;
    NE_u3=0;
    NE_scA=0;
    NE_scB=0;
    NE_scC=0;
    NE_scD=0;
end;

Game III payoff_calc.m

function [NaN_check, dominant, log_LP, b, V_claimed, u1, u2, u3, NE_check_2p,
scenarioA, scenarioB, scenarioC, scenarioD] = payoff_calc(fixed, variable,
theta, rho, alpha, kappa, action_ones, theta_set, size_actions, size_A1,
size_A2)

%SET INPUTS

%Fixed
max_horizon = fixed(1,1);
max_theta = fixed(2,1);
tauhat_l = fixed(3,1);
R_0 = fixed(4,1);
V_0 = fixed(5,1);
p1 = fixed(6,1);
p2 = fixed(7,1);
etahat_L = fixed(8,1);
etahat_H = fixed(9,1);

%Variable

%variable = [lambda_1; Vhat; L; P; value_vector; bathtub_vector];
lambda_1 = variable(1,1);
Vhat = variable(2,1);
Lprime = variable(3,1);
P = variable(4,1);
value=variable(5:5+(max_theta/3)-1);
bathtub = variable(5+(max_theta/3):52);
value_shape=variable(53,1);
bathtub_shape=variable(54,1);
D_0prime = variable(55,1);
q = variable(56,1);
a = variable(57,1);
alpha = variable(58,1);
delta = variable(59,1);
HofV_thetamax = variable(60,1);
V_claimed_min=variable(61,1);

if (1-D_0prime)/q < 1
D_flag=1;
else D_flag=0;
end

Lprime = repmat(Lprime,size_actions(1,1),size_actions(1,2));
P = repmat(P,size_actions(1,1),size_actions(1,2));
D_Oprime = repmat(D_Oprime,size_actions(1,1),size_actions(1,2));

%Define actual value;
value_lookup = [theta_set', value];
V = zeros(size_actions(1,1),size_actions(1,2));
temp_i = 1;
temp_j = 1;
while temp_i <= size_actions(1,1)
    while temp_j <= size_actions(1,2)
        [valuei, valuej] = find(value_lookup(:,1)==theta(temp_i,temp_j));
        V(temp_i,temp_j) = value_lookup(valuei,2);
        temp_j = temp_j+1;
    end
    temp_i = temp_i+1;
    temp_j = 1;
end

%Define b for physician payoff -- function of V
b = (log((action_ones+V)./D_Oprime))./(log(Lprime./P));
log_LP = (log(Lprime./P));

%Define claimed value -- function of V and delta
delta = repmat(delta,size_actions(1,1),size_actions(1,2));
V_claimed = max(V_claimed_min,V+delta);
%V_claimed_check = V_claimed > 0 ;
%V_claimed = V_claimed .* V_claimed_check;

%Define probability of switching hospitals
HofV_theta = (HofV_thetamax/Vhat).*V;

kappa_check=single((kappa/.25)+0.8);

%Define y
kappa = repmat(kappa,size_actions(1,1),size_actions(1,2));
y = kappa < V_claimed;

%Define x1 binary variable
x1 = zeros(size_actions(1,1),size_actions(1,2));
[i4,j4] = find(rho<omega);
temp = 1;
while temp <= length(i4)
    x1(i4(temp),j4(temp)) = 1;
    temp = temp+1;
end

%Define y(1-x1)
scenarioD = y.*(ones(size_actions(1,1),size_actions(1,2))-x1);
%and also other 3 scenarios
scenarioA = (ones(size_actions(1,1),size_actions(1,2)) - y) .* (x1);
scenarioB = (ones(size_actions(1,1),size_actions(1,2)) - y) .* (ones(size_actions(1,1),size_actions(1,2)) - x1);
scenarioC = y .* x1;

%DEFINE MANUFACTURER PAYOFF
%Define probability of leaving
Pr_leavelookup = [theta_set', bathtub];
Pr_leave = zeros(size_actions(1,1),size_actions(1,2));
temp_i = 1;
temp_j = 1;
while temp_i <= size_actions(1,1)
    while temp_j <= size_actions(1,2)
        [bathtubi, bathtubj] = find(Pr_leavelookup(:,1) == theta(temp_i,temp_j));
        Pr_leave(temp_i,temp_j) = Pr_leavelookup(bathtubi,2);
        temp_j = temp_j + 1;
    end
    temp_i = temp_i + 1;
    temp_j = 1;
end

%Define parameters for adoption time pdf
lambda_1 = repmat(lambda_1,size_A1, size_A2);
lambda_2 = lambda_1;
tauhat_1 = repmat(tauhat_1,size_A1, size_A2);
tauhat_2 = 2*omega;

%IF(rho<2*omega, rho, 2*omega)
rho_le2omega = le(rho, 2*omega);
tau = (rho_le2omega.*rho) + ((1 - rho_le2omega).*2.*omega);

% Calculate u1
Pr_time = betacdf(((tau - tauhat_1)./(tauhat_2 - tauhat_1)), lambda_1, lambda_2);
u1 = (ones(size(omega)) - Pr_leave) .* Pr_time .* V_claimed;
u1_ABC = round(u1.*1000000000000000)/1000000000000000;
u1_D = u1_ABC.*HofV_theta;
u1 = ((ones(size_actions(1,1),size_actions(1,2)) - scenarioD).*u1_ABC) + (scenarioD.*u1_D);

NaN_check = zeros(1,3);
u1_NaN = isnan(u1);
NaN_check(1,1) = sum(sum(u1_NaN));

%DEFINE PHYSICIAN PAYOFF
%Define D
if D_flag == 0;
    q = repmat(q,size_actions(1,1),size_actions(1,2));
    [i3,j3] = find(omega<((ones(size_actions(1,1),size_actions(1,2)) - D_0prime)./q));  %Defining breakpoints for piecewise D function
    D_break = max(j3);
D = zeros(size_actions);
D(:,1:D_break) = D_0prime(:,1:D_break)+(q(:,1:D_break).*omega(:,1:D_break));
D(:,D_break+1:end) = 1;
else if D_flag == 1
    D = ones(size_actions);
end;
end;

%Define x2 binary variable
x2 = zeros(size_actions(1,1),size_actions(1,2));
[i5,j5] = find((theta+rho)<((ones(size_actions(1,1),size_actions(1,2))+V)./D_0prime).^(ones(size_actions(1,1),size_actions(1,2))./b))-(D./D_0prime).^(ones(size_actions(1,1),size_actions(1,2))./b))+omega);
temp = 1;
while temp <= length(i5)
    x2(i5(temp),j5(temp)) = 1;
    temp = temp+1;
end

%Define limit 1
lim_1 = (x1.*rho)+((action_ones-x1).*omega);

%Define limit 2
maxval_pt = (((action_ones+V)./D_0prime).^(action_ones./b))-(D./D_0prime).^(action_ones./b)+omega;
lim_2 = (x1.*rho)+(action_ones-x1).*((x2.*(theta+rho))+((action_ones-x2).*maxval_pt));

%Define limit 3
lim_3 = (x1.*rho)+((action_ones-x1).*(theta+rho));

%Calculate u2
%Calculate 1st piece of E(R(tau))
R_0 = repmat(R_0,size_actions(1,1),size_actions(1,2));
ERtau_1 = lim_1.*R_0;

%Calculate 2nd piece of E(R(tau))
ERtau_2 = zeros(size_actions(1,1),size_actions(1,2));
[i6,j6] = find(lim_2-lim_1 > zeros(size_actions(1,1),size_actions(1,2)));
temp = 1;
%(((R0*(1-omega+lim2)^(1+b))/(1+b))-((R0*(1-omega+lim 1)^(1+b))/(1+b)))
while temp <= length(i6)
    m = i6(temp);
    n = j6(temp);
    ERtau_2(m,n) = (((D_0prime(m,n)*R_0(m,n)*((D(m,n)/D_0prime(m,n))^((1/b(m,n))-omega(m,n)+lim_2(m,n)))/(b(m,n)+1))-
        ((D_0prime(m,n)*R_0(m,n)*((D(m,n)/D_0prime(m,n))^((1/b(m,n))-omega(m,n)+lim_1(m,n)))/(b(m,n)+1))));
    temp = temp+1;
end
%Calculate 3rd piece of E(R(tau))
ERtau_3 = (lim_3 - lim_2).*(action_ones+V).*R_0;

%u2
u2 = R_0.*ones(size_actions(1,1),size_actions(1,2));
[i7,j7] = find(lim_3 ~= zeros(size_actions(1,1),size_actions(1,2)));
temp = 1;
while temp <= length(i7)
    u2(i7(temp),j7(temp)) =
    (1/(lim_3(i7(temp),j7(temp))))*(ERtau_1(i7(temp),j7(temp))+ERtau_2(i7(temp),j7(temp)));
temp = temp+1;
end
u2_ABC = round(u2.*1000000000000000)/1000000000000000;

%DEFINE HOSPITAL PAYOFF
z1=(ones(size_actions(1,1),size_actions(1,2))-y).*lim_1 + (y.*lim_3);
z2=lim_3;
M_part1=(R_0.*z1);
M_part2=R_0.*(V_claimed+ones(size_actions(1,1),size_actions(1,2))).*(z2-z1);
My0_part1=(R_0.*lim_1);
My0_part2=R_0.*(V_claimed+ones(size_actions(1,1),size_actions(1,2))).*(z2-lim_1);
alpha = repmat(alpha,size_actions(1,1),size_actions(1,2));
lim_3_check= lim_3~=0;
M=R_0.*ones(size_actions(1,1),size_actions(1,2)).*lim_3_check;
My1 = M;
My0=M;
[i11,j11] = find(z2 ~= zeros(size_actions(1,1),size_actions(1,2))); temp = 1;
while temp <= length(i11)
    M(i11(temp),j11(temp)) =
    (1/(z2(i11(temp),j11(temp))))*(M_part1(i11(temp),j11(temp))+M_part2(i11(temp),j11(temp)));
    My0(i11(temp),j11(temp)) =
    (1/(z2(i11(temp),j11(temp))))*(My0_part1(i11(temp),j11(temp))+My0_part2(i11(temp),j11(temp)));
    temp = temp+1;
end
u3_ABC=alpha.*u2 - (ones(size_actions(1,1),size_actions(1,2))-alpha).*M;
u3My1=alpha.*R_0 - (ones(size_actions(1,1),size_actions(1,2))-alpha).*My1;
u3My0=alpha.*u2_ABC - (ones(size_actions(1,1),size_actions(1,2))-alpha).*My0;
u3_D=(u3My1.*(ones(size_actions(1,1),size_actions(1,2))-HofV_theta))- (u3My0.*HofV_theta);
u3=((ones(size_actions(1,1),size_actions(1,2))-scenarioD).*u3_ABC)+(scenarioD.*u3_D);

if kappa(1:1)==105
save('u3','u3','-ascii','-double');
end;

u3_NaN = isnan(u3);
NaN_check(1,3) = sum(sum(u3_NaN));

%FIND BEST CHOICES FOR PLAYERS 1 & 2
 dominant = zeros(1,3);
%Find max values of u1 across each player 2 actions
 maxu1_xa2 = max(u1);
 u1max_mat = zeros(size_actions(1,1),size_actions(1,2));
 u1max_mat_ind = zeros(size_actions(1,1),size_actions(1,2));
 i8=zeros(1,1);
 j8=zeros(1,1);
 temp = 1;
 while temp <= size_actions(1,2)
   [i8_temp,j8_temp] = find(u1(:,temp) == maxu1_xa2(1,temp));
   j8_temp = temp.*j8_temp;
   i8 = [i8;i8_temp];
   j8 = [j8;j8_temp];
   temp = temp + 1;
 end
 i8 = i8(2:end);
 j8 = j8(2:end);

if i8(:,1) == i8(1,1)
  dominant(1,1) = 1;
end

temp = 1;
while temp <=length(i8)
  u1max_mat(i8(temp),j8(temp)) = u1(i8(temp),j8(temp));
  u1max_mat_ind(i8(temp),j8(temp)) = 1;
  temp = temp + 1;
end

%Find max values of u2 across each player 1 actions
 maxu2_xa1 = max(u2,[],2); %Find max values for each action
 maxu2_xa1 = maxu2_xa1'; %Transpose
 u2max_mat = zeros(size_actions(1,1),size_actions(1,2)); %keep max value payoffs for each value
 u2max_mat_ind = zeros(size_actions(1,1),size_actions(1,2)); %one/zero to indicate max locations
 i9=zeros(1,1);
 j9=zeros(1,1);
 temp = 1;
 while temp <= size_actions(1,1)
   [i9_temp,j9_temp] = find(u2(temp,:) == maxu2_xa1(1,temp)); %find locations of max values
   i9_temp = temp.*i9_temp;
 end
i9 = [i9, i9_temp];
j9 = [j9, j9_temp];
temp = temp + 1;
end
i9 = i9(2:end);
j9 = j9(2:end);
temp = 1;
if j9(1,:) == j9(1,1);
    dominant(1,2) = 1;
end

while temp <= length(i9)
    u2max_mat(i9(temp), j9(temp)) = u2(i9(temp), j9(temp));
    u2max_mat_ind(i9(temp), j9(temp)) = 1;
    temp = temp + 1;
end

% Identify NE candidates based upon u1, u2 calcs
NE_check_2p = u1max_mat_ind.*u2max_mat_ind;

Game III pareto_rank.m

% Read in file
clear
load ffe_output.dat;

% Arrange so each trial is segmented

size_input = size(ffe_output);
num_rows = size_input(1,1);
num_trials = max(ffe_output(:,1));  % Calculate number of trials
trial_counter = 1;
trial_NEnum = zeros(1);
itr_a = 0;
while trial_counter <= num_trials  % For each trial
    itr_a = itr_a + 1;
    [temp_i, temp_j] = find(ffe_output(:,1) == trial_counter);
    trial_NEnum(itr_a, 1) = max(temp_i);
    trial_counter = trial_counter + 1;
end
trial_NEnum = [trial_NEnum; trial_NEnum(end)*2];
trial_NEnum_shift = [0; trial_NEnum(1:end-1,1)];
segments = trial_NEnum - trial_NEnum_shift;
[temp_i, temp_j] = size(segments);
segments = segments(1:temp_i-1, 1);
max_numNE = max(segments);
NE_cell = mat2cell(ffe_output, segments', size_input(1,2));

% Rank NE for each trial
itr_b = 1;
while itr_b <= num_trials
%For each trial
ite_b;
trial_matrix=cell2mat(NE_cell(itr_b));
[size_i, size_j]=size(trial_matrix);
temp_matrix=trial_matrix;
temp_matrix(:,size_j+1)=zeros(size_i,1);
trial_matrix2=zeros(1,size_j+1);
rank=1;
num_NE=size_i;
last_flag=0;
error_flag=0;

if temp_matrix(1,2)~=0
%For subset
while last_flag==0
  %rank
  temp_u1=temp_matrix(:,17);
  temp_u2=temp_matrix(:,18);
  temp_u3=temp_matrix(:,19);
  %check for outright winners
  maxu1=max(temp_u1);
  maxu2=max(temp_u2);
  maxu3=max(temp_u3);
  if maxu1==0
    if temp_matrix(1,2)~=0
      error_flag = 1;
    end;
  end;
  if maxu2==0
    if temp_matrix(1,2)~=0
      error_flag = 1;
    end;
  end;
  if maxu3==0
    if temp_matrix(1,2)~=0
      error_flag = 1;
    end;
  end;
  maxchecku1=maxu1/maxu1;  %won't work if max = 0
  maxchecku2=maxu2/maxu2;
  maxchecku3=maxu3/maxu3;

  %length = length(temp_u1)
  %test1=[temp_u1, repmat(maxu1,length,1), maxchecku1];
  %test2=[temp_u2, repmat(maxu2,length,1), maxchecku2];
  %test3=[temp_u3, repmat(maxu3,length,1), maxchecku3];
  %test = [test1, test2, test3]

  maxchecku1(maxchecku1==1)=0;
  maxchecku2(maxchecku2==1)=0;
  maxchecku3(maxchecku3==1)=0;
  rank_mat=rank*ones(length(temp_u2),1);
  Branked= maxchecku1.*maxchecku2.*maxchecku3.*rank_mat;
%if nothing was ranked because there were ties
if sum(Branked)==0
    dominated_check = maxchecku1+maxchecku2+maxchecku3;
    nondominated=zeros(size(dominated_check));
    nondominated(dominated_check==0)=1;
    rank_mat=rank*ones(length(temp_u2),1);
    Branked= rank_mat.*nondominated;
end

temp_matrix(:,size_j+1)=temp_matrix(:,size_j+1)+Branked;

% keep only unranked rows
sortcol=size(temp_matrix,2);
 temp_matrix_sorted = sortrows(temp_matrix,-sortcol);

if isempty(temp_matrix_sorted)
    last_flag=1;
end

[temp_ib, temp_jb]=find(temp_matrix_sorted(:,size_j+1)==0);
if isempty(temp_ib)
    last_flag=1;
end
if last_flag==0
    last_flag = isempty(temp_ib);
end
if last_flag==0
    min_row = min(temp_ib);
    temp_matrix=temp_matrix_sorted(min_row:end,:);
    trial_matrix2=[trial_matrix2;temp_matrix_sorted(1:min_row-1,:)];
end
if last_flag==1
    trial_matrix2=[trial_matrix2;temp_matrix_sorted(1:end,:)];
end

rank=rank+1;
end
end
if temp_matrix(1,2)==0
    trial_matrix2=[trial_matrix,0];
end;
trial_matrix2 = trial_matrix2(2:end,:);
NE_cell(itr_b,1)=mat2cell(trial_matrix2);
error_flag_array(itr_b,1)=error_flag;

%trial_matrix2 = trial_matrix2(:,26);
itr_b=itr_b+1
end
pareto_rank_out=cell2mat(NE_cell);
save('error_flag_array.txt', 'error_flag_array', '-ascii', '-double');
save('pareto_rank_output.txt','pareto_rank_out','-ascii', '-double');
References


